Minimum Wages and Rents

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In this note we lay down the main theoretical framework and empirical strategy for the project.

Theoretical Framework

We are interested in the short-run effects of increases in minimum wages on a ZIP code's rental market. Residents in this ZIP code potentially work in some other ZIP code, under a different minimum wage policy. We let $z \in \mathcal{Z}_i$ be workplaces of residents of i, $\underline{w}_i$ be the MW binding at ZIP code i and $\underline{w}_{z z \in \mathcal{Z}_i}$ the one binding at each workplace. Residents of i meet in a single market to rent square feet, with equilibrium rents per square foot r_i given by

$$\sum_{z \in \mathcal{Z}_i} L_{iz} h_{iz}(r_i, p_i, y_z) = D_i(r_i),$$

where p_i and y_z are prices of local consumption goods, and income of people working in z. L_{iz} are (exogenus) measures of workers commuting to z (where $L_i = \sum_z L_{iz}$ are i's residents), and $h_{iz}(\cdot)$ are housing demand functions.

Under the assumption that $p_i = p_i(\underline{w}_i)$ and $y_z = y_z(\underline{w}_z)$, both increasing, we can use the equilibrium condition to write a change in the log of rents as

$$\Delta \ln r_i = \gamma_i \Delta \ln \underline{w}_i + \beta_i \sum_z \pi_{iz} \Delta \ln \underline{w}_z$$

where β_i and γ_i are parameters that depend on elasticities, and $\pi_{iz} = L_{iz}/L_i$ are commuting shares.[1] It turns out that, if $\partial h_{iz}/\partial p_i < 0$ and $\partial h_{iz}/\partial y_z > 0$, then $\gamma_i < 0$

[1] We also need to assume that the elasticity of housing demand to income doesn't vary by z,

and $\beta_i > 0$.

As a result of this exercise, we expect workplace and residence MW changes to have opposing effects on rental prices.

Data

Our main data sources are:

- Unbalanced panel of ZIP codes with median rents in SFCC category from Zillow, at a monthly frequency, from February 2010 until December 2019.
- Balanced panel of binding minimum wages in each ZIP code for the same period.
- Origin-destination matrix of commuting shares between pairs of ZIP codes constructed from LODES for each year between 2009 and 2018.

We use this data to compute the "experienced log minimum wage" for each ZIP code, given by $\underline{w}_{it}^{exp} = \sum_{z \in \mathcal{Z}_i} \pi_{iz} \ln \underline{w}_z$. Figure 1 illustrates this variable using the New York–New Jersey metro area around January 2019, when there were increases of the MW in New York City and New York State.

Empirical Approach

We are interested in models of the form

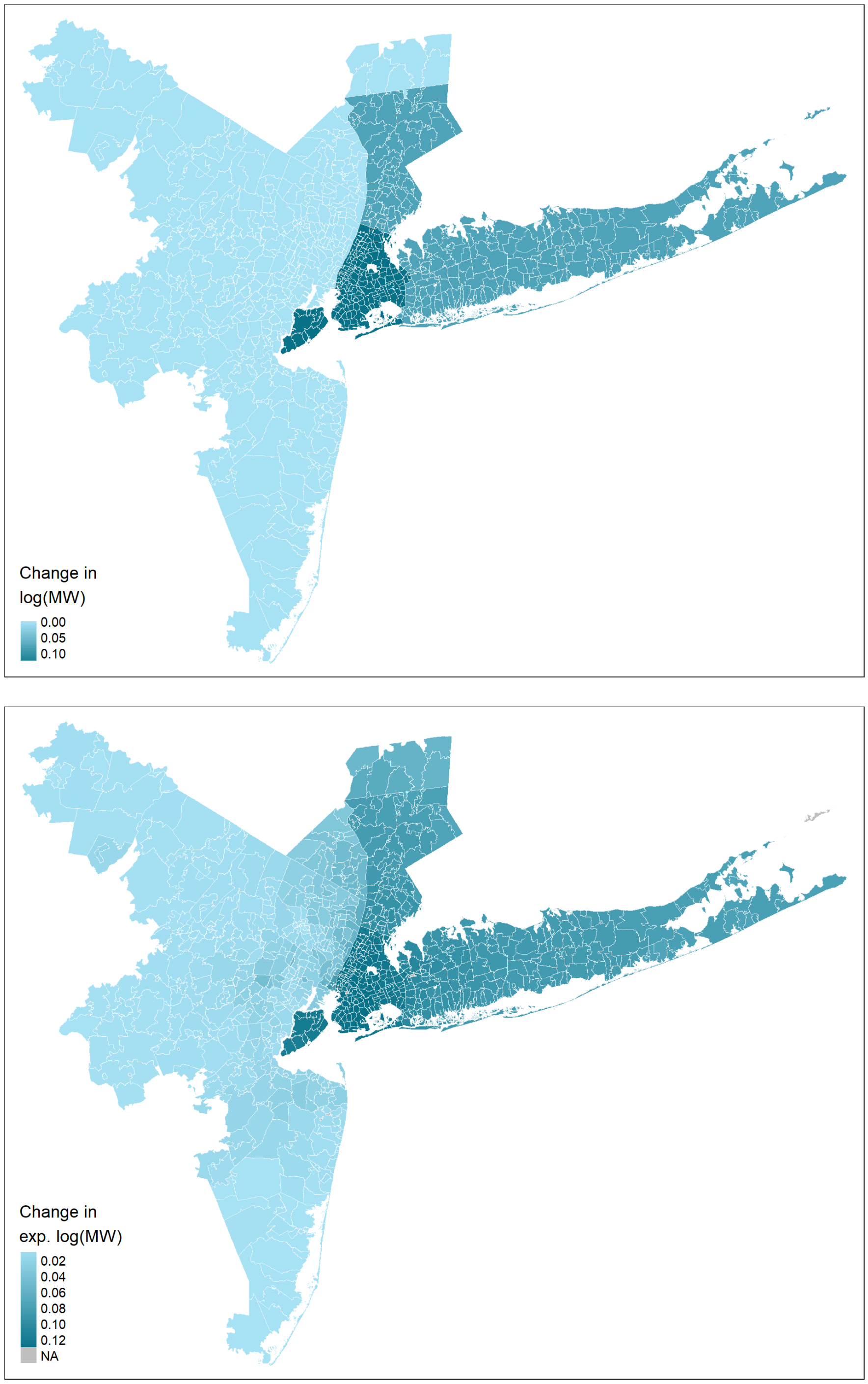
$$\ln r_{it} = \alpha_i + \tilde{\delta}_t + \gamma \ln \underline{w}_i + \beta \underline{w}_{it}^{exp} + \epsilon_{it}$$

where i is ZIP code and t is monthly data. We sometimes include time-varying covariates or allow time effects to vary by some wider geography (state, CBSA). Taking first differences, we get:

$$\Delta \ln r_{it} = \delta_t + \gamma \Delta \ln \underline{w}_i + \beta \Delta \underline{w}_{it}^{exp} + \Delta \epsilon_{it}$$

where $\tilde{\delta}_t = \delta_t - \delta_{t-1}$. We use a first-differences specification because we expect the unobserved zipcode-month rental shocks to be correlated over time. Furtermore, we detected strong correlation of local rents over time.

Figure 1: Actual and Experienced MW changes between December 2018 and January 2019 in the New York metro area



Source: World Bank

Table 1: Static model

	$\Delta \underline{w}_{ict}^{\text{exp}}$	$\Delta \ln r_{ict}$		
	(1)	(2)	(3)	(4)
$\Delta \ln \underline{w}_{ict}$	0.8718	0.0257		-0.0320
	(0.0296)	(0.0137)		(0.0163)
$\Delta \underline{w}_{ict}^{\text{exp}}$			0.0320	0.0662
			(0.0151)	(0.0278)
$\Delta \ln \underline{w}_{ict} + \Delta \underline{w}_{ict}^{\text{exp}}$				0.0342
				(0.0153)
County-quarter controls	Yes	Yes	Yes	Yes
P-value equality				0.0272
R-squared	0.9469	0.0209	0.0209	0.0209
Observations	131,196	131,196	131,196	131,196

Notes:

We estimate this model under an unbalanced, partially balanced and fully balanced panels of the Zillow rents data and we consistently obtain negative estimates for γ and positive ones for β. Table 1 shows the main results using a partially balanced panel, with all ZIP codes in the data as of July 2015, and some economic controls from the QCEW.

Finally, once we estimated our preferred model, we want to compute ZIP code-specific MW-to-rents pass-through coefficients for a counterfactual increase in the federal minimum wage (using ZIP code-month IRS data on income).

Because we are dealing with a staggered continuous treatment that spills over across metropolitan areas, it is not entirely obvious whether our estimation strategy is actually computing what we want. Our questions are:

1. Does the distribuited lag FE estimator correctly identifies γ and β parameters from an underlying causal model?

2. To deal with the issues generated by the staggered nature of out treatment, should we implement an alternative estimation approach where we restrict the units we use as controls for each treatment? As we are interested in two variables (a direct effect and a spillover) it is not obvious what is the best way to define cleanly the control units. We thought of (i) a stacking method as in Cegniz et

al (2019), (ii) using the imputation method in Borusyak et al (2021).

3. Should we focus the problem from the perspective of accounting for spillovers, *a la* Butts (2021), where we aim at estimating the effect of same-unit MW, and the spillovers are like an incidental parameter problem? We find it more appealing from an economic theory perspective to estimate the effect of both workplace and residence MW changes, but we could impose some structure on the spillovers and try to estimate the direct effect and the spillovers separately.

To illustrate our initial thinking, in the appendix we lay a formal causal model in which we discuss what conditions are necessary to identify both γ and β in our model.

References

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess 2021. Revisiting Event Study Designs: Robust and Efficient Estimation.

Butts, Kyle 2021. Difference-in-Differences Estimation with Spatial Spillovers.

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

Appendix: Identification with continouos treatment and spillovers across units

Consider the causal model for rents given by

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

where w gives the “dose” of treatment ZIP code i receives at time t. We impose some structure by assuming that

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

where α_i and δ_t are fixed effects, π_{ij} is the (fixed) share of i residents that work in j, known to the econometrician, and γ and β are parameters. Note that this potential outcomes model assumes that the direct effect of treatment equals $\gamma + \beta\pi_{ii}$ and the effect of treatment somewhere else (the “spillover”) equals $\beta\pi_{iz}$.

Indentification under a simple example with 3 ZIP codes and 2 time periods

Suppose an hypothetical metropolitan area with 3 ZIP codes and two consecutive periods (period 0 and 1), such that $r_{it} = Y_{it}(w_{1t}, w_{2t}, w_{3t})$. Suppose that in period 0 the MW is \$0 everywhere, but in period 1 the MW in unit 2 increases to $w_{21} = \$1$. Then, we have the following data:

- $Y_{10}(0,0,0) = \alpha_1 + \delta_0$ and $Y_{11}(0,1,0) = \alpha_1 + \delta_1 + \beta\pi_{12}$
- $Y_{20}(0,0,0) = \alpha_2 + \delta_0$ and $Y_{21}(0,1,0) = \alpha_2 + \delta_1 + \gamma + \beta\pi_{22}$
- $Y_{30}(0,0,0) = \alpha_3 + \delta_0$ and $Y_{31}(0,1,0) = \alpha_3 + \delta_1 + \beta\pi_{32}$

Taking time differences, and denoting $\delta = \delta_1 - \delta_0$, we have

- $Y_{11} - Y_{10} = \delta + \beta\pi_{12}$
- $Y_{21} - Y_{20} = \delta + \gamma + \beta\pi_{22}$
- $Y_{31} - Y_{30} = \delta + \beta\pi_{32}$

Can we identify β and γ? Yes, as we have 3 unknown parameters (δ, β, γ) and 3 equations. Algebra implies that

$$\beta = \frac{(Y_{11} - Y_{10}) - (Y_{31} - Y_{30})}{\pi_{32} - \pi_{12}}$$

and that

$$\begin{aligned}
\gamma &= (Y_{21} - Y_{20}) - \beta\,(Y_{11} - Y_{10}) \\
&= (Y_{21} - Y_{20}) - \left[\left(\frac{\pi_{32} - \pi_{22}}{\pi_{32} - \pi_{12}}\right)(Y_{11} - Y_{10}) + \left(\frac{\pi_{22} - \pi_{12}}{\pi_{32} - \pi_{12}}\right)(Y_{31} - Y_{30})\right]
\end{aligned}$$

The workplace MW parameter β is identified off of the difference-in-differences between control units, adjusted by exposure to the treatment in unit 2. The residence MW parameter γ is identified by substracting from the difference in unit 2 a weighted mean difference between units 1 and 3, where the weights reflect how much treatment they received relative to unit 2.

Note that we need to assume that $\pi_{32} - \pi_{12} \neq 0$. If this is not the case β is not identified from the comparison of untreated units.