Minimum Wages and Rents

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In this note we lay down the main theoretical framework and empirical strategy for the project. We lay down a few questions related to the latter.

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 ones 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. $L_{iz z\in\mathcal{Z}_i}$ are (exogenous) measures of workers commuting to z ($L_i = \sum_{z\in\mathcal{Z}_i} L_{iz}$ are i's residents), and $h_{iz}(\cdot)_{z\in\mathcal{Z}_i}$ 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

$$d\ln r_i = \gamma_i d\ln \underline{w}_i + \beta_i \sum_{z\in\mathcal{Z}_i} \pi_{iz} d\ln \underline{w}_z$$

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 $\underline{w}_{it}^{exp} = \sum_{z \in \mathcal{Z}_i} \pi_{iz} \ln \underline{w}_z$, using the shares for a given year. As an illustration, Figure 1 maps the experience MW variable in 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

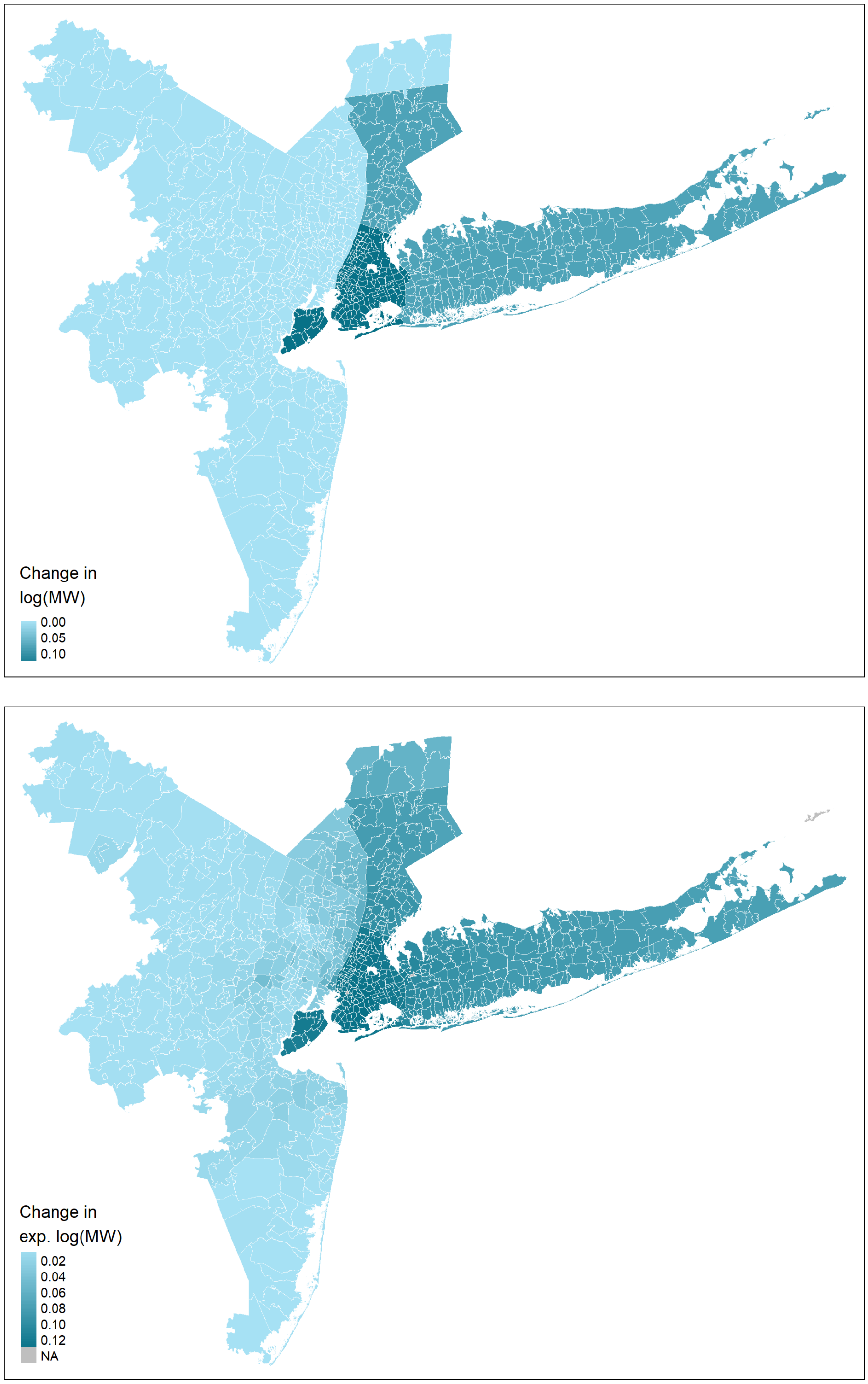
$$\ln r_{it} = \alpha_i + \tilde{\delta}_t + \gamma \ln \underline{w}_{it} + \beta \underline{w}_{it}^{exp} + \epsilon_{it}$$

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

$$\Delta \ln r_{it} = \delta_t + \gamma \Delta \ln \underline{w}_{it} + \beta \Delta \underline{w}_{it}^{exp} + \Delta \epsilon_{it} \tag{1}$$

where $\delta_t = \tilde{\delta}_t - \tilde{\delta}_{t-1}$. We use a first-differences specification because we expect the unobserved shocks in the levels equation to be positively 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



Notes: The top figure shows changes in the binding MW in each ZIP code in the New York-New Jersey metro area. The bottom figure shows changes in the "experienced" log MW, constructed using commuting shares for 2017 from LODES.

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 Zillow data as of July 2015, and some economic controls from the QCEW that vary at the county and quarter levels.[2] When extending the model to add leads and lags of the MW variables we obtain coefficients that are statistically equal to zero for both, while γ and β remain very similar.

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:

Finally, after converging a model that we trust, we plan to compute ZIP code-specific MW-to-rents pass-through coefficients for a counterfactual increase in the federal minimum wage (using ZIP code-year IRS data to estimate the elasticity of income to the minimum wage).

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 differenced estimator from (1) correctly identifies the parameters γ and β from an underlying causal model? The main complication we note is that, in each event, this estimator compares units that are treated directly, some that

[2]Results without the controls look very similar.

are treated indirectly, some that are not treated, and some that were treated before but had no MW change recently.

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 that we use as controls for each treatment? Treatment effect heterogeneity or dynamic effects might potentially bias our estimates. As we are interested in two variables (the "residence" and "workplace" MWs) 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 think of this problem as estimation of the effect of same-unit MW controlling for spillovers across units (e.g., Butts 2021)? However, we find it more appealing from an economic theory perspective to estimate the effect of both workplace and residence MW changes.

4. Should we more seriously try to map the theoretical model to the empirical one? We could develop a microfoundation starting from a worker's utility similar to Madera et al (2021). A shortcoming is that the theoretical model assumes people only consume in their residence ZIP code, which is clearly not true. One could even think of a "consumption MW" which would average minimum wage levels using shares of non-tradable consumption in every other ZIP code.

To illustrate our initial thinking, in the appendix we lay out a formal causal model in which we discuss identification of both γ and β for a 3 units example.

Appendix: Identification with continouos treatment and spillovers across units

Consider the causal model for rents given by

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

where w gives the "dose" of treatment ZIP code i receives at time t and $\mathcal{Z}$ is the total number of units. We impose some structure by assuming that

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

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, and γ and β are scalar parameters. (We assume away unobservables to develop the example below.) 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 simple example with 3 ZIP codes and 2 time periods

Consider a 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 a difference-in-differences between units that are not treated directly, adjusted by exposure to the treatment in unit 2. No "never treated" units are required. 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.

References

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