Do Minimum Wages Increase Rents?

Evidence from US ZIP Codes Using High-Frequency Data

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Motivation

Research on minimum wage (MW) has mostly focused on employment.

However, MW policies are *place-based*, so one should expect broader effects in the local economy:

$\Rightarrow$ Housing market.

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⇒ Housing market.

Prediction from theory
A canonical version of the (Muth-Mills) monocentric city model suggests that income increases will pass-through 1:1 to rents (Brueckner et al. 1987).

This paper

We investigate the short term effects of MW policies on rents in the US:

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- Estimate pass-through of MW increases to rents.

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To do so, we:

- Exploit high-frequency (monthly) high-resolution (ZIP Code) rents data from Zillow.
- Leverage timing and spatial variation in MW changes *within* metropolitan areas.
- Propose a novel model-based measure of exposure to MW changes based on commuting shares.

Comparative statics intuition

Think of a metropolitan area, and a MW increase in the business district (CBD).

Partial equilibrium: short term

- Firms producing in the CBD will pay a higher wage. Income redistribution from firms to low income workers.
- Income changes are heterogeneous across space because people work and reside in different locations.
- Housing is a normal good. Housing demand in some areas increases and landlords charge a higher rent.

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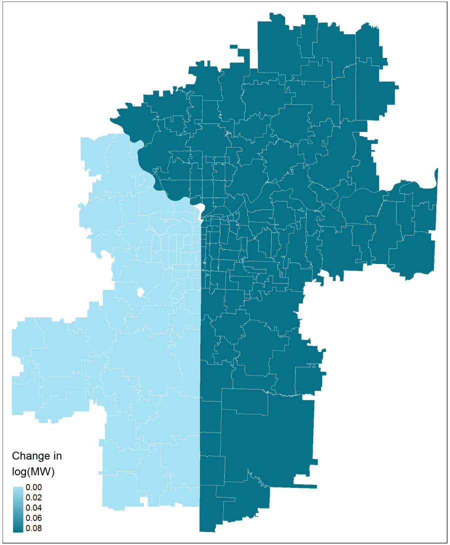
General equilibrium: long term (Not this paper!)

- People change residence and workplace locations (sorting).
- Developers build more houses (supply response).

A motivating example

Kansas City lies between the state of Kansas and the state of Missouri. In January 2019, the state of Missouri raised the MW from \$7.85 to \$8.60, while in the state of Kansas the binding MW was (and still is!) the federal one of \$7.25.



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However, MW workers in the Missouri side of Kansas city may also live in the state of Kansas. $\rightarrow$ We need to take the commuting structure into account!

A new model-based measure of exposure to MW

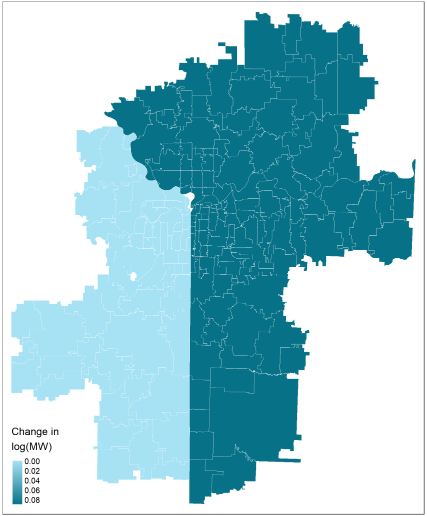
For ZIP code i, and month t we define it as

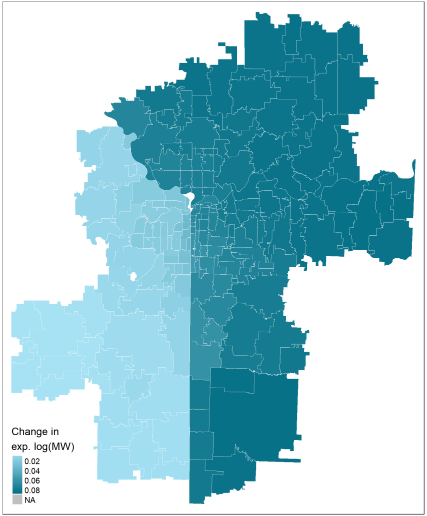
$$\underline{w}_{it}^{\text{exp}} = \sum_{z \in \mathbb{Z}_i} \pi_{iz} \ln \underline{w}_{zt} \ ,$$

where

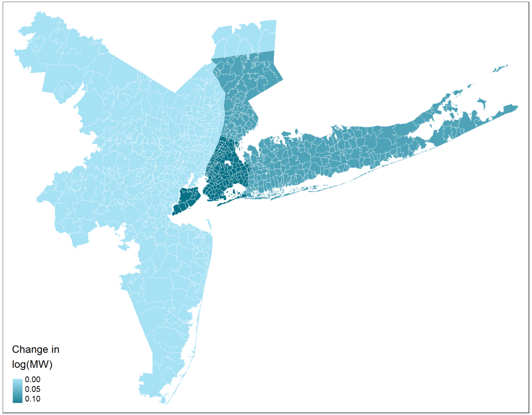
- $\mathbb{Z}_i$ are workplace locations of i's residents, and
- $\pi_{iz} = \frac{L_{iz}}{L_i}$ is the share of i's residents who work in z.

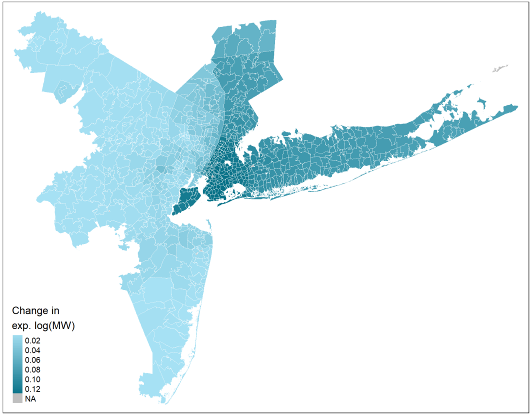
A motivating example (Continuation)



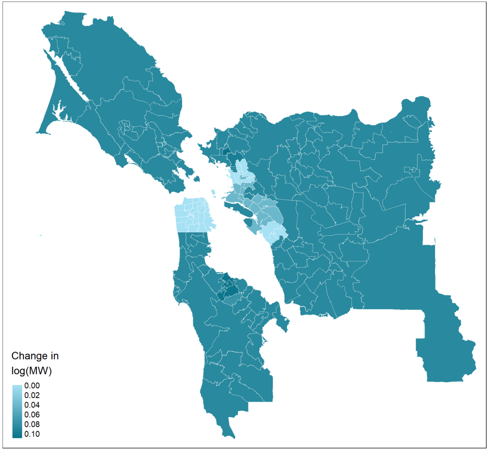


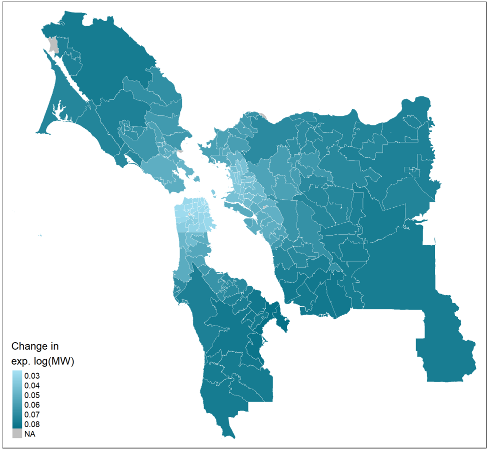
Other examples: New York (MW Changes in January 2019)





Other examples: Bay area (MW Changes in January 2019)





Outline

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Counterfactuals

Model

Data

Zillow Data

- Leader online real estate and rental platform in the U.S. (more than 110 million homes and 170 million unique monthly users in 2019).
- Provides *median* rents data at ZIP code, county, and state levels at a monthly frequency for several housing categories.

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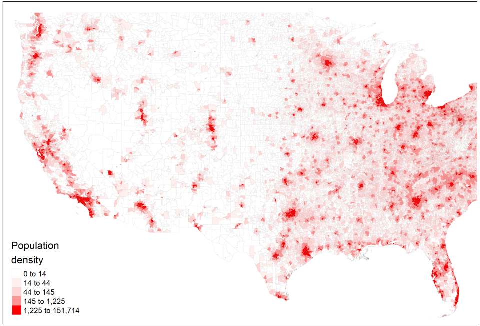
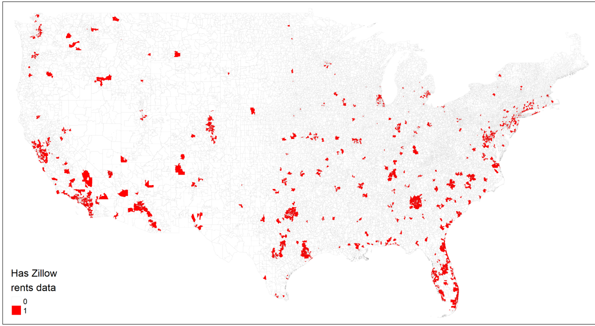
  - Most populated series in Zillow.
- Limitation: Zillow sample is not random.

Comparison between Zillow Sample and Population Density





The Statutory MW

- Collect MW data at state, county and city levels between Jan 2010 and Dec 2019.
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- Assign those data to ZIP codes.
- Define statutory MW in ZIP code as maximum between state and local levels.
- ZIP codes available in Zillow contain 18,689 changes at the ZIP code-month level.
  - 151 state-level changes.
  - 182 county- and city-level changes.

Using LODES to construct the experienced log MW

Construct **origin-destination matrix** at ZIP code level from 2017 LODES. Observe:

- Number of workers residing in a ZIP code and working in every other ZIP code.
- Analogous, matrix for number of workers younger than 29 and earning less than $1,251.

Other Data Sources

- Economic controls from the Quarterly Census of Employment and Wages (QCEW).
- IRS Statistics of income - ZIP Code Aggregates (New)
- ZIP Code Month panel of rents since 2018 from actual transactions data (New)

Empirical Strategy

Empirical (Naive) model

Ignoring the experienced MW, one may estimate the following first differences model:

$$\Delta \ln r_{it} = \tilde{\delta}_t + \tilde{\beta} \Delta \ln \underline{w}_{it} + \Delta \mathbf{X}'_{c(i)t} \tilde{\eta} + \Delta \tilde{\varepsilon}_{it},$$

where

- ZIP code i, county $c(i)$, month t;
- r_{it}: rents per square foot;
- $\ln \underline{w}_{it}$: statutory log MW;
- $\tilde{\delta}_t$: month fixed effects (ZIP code FE $\tilde{\alpha}_i$ is implicit);
- $\mathbf{X}_{c(i)t}$: time-varying controls.

Empirical model

Now add experienced MW:

$$\Delta \ln r_{it} = \delta_t + \beta \Delta \underline{w}_{it}^{\text{exp}} + \gamma \Delta \ln \underline{w}_{it} + \Delta \mathbf{X}'_{c(i)t}\eta + \Delta \varepsilon_{it},$$

where $\underline{w}_{it}^{\text{exp}}$ is experienced log MW (Recall $\Delta \underline{w}_{it}^{\text{exp}} = \sum_{z \in \mathbb{Z}_i} \pi_{iz} \Delta \ln \underline{w}_{zt}$).

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For causal effect of β we need:

$$E \left[\Delta \varepsilon_{ict} \Delta \underline{w}_{ic\tau}^{\exp} \middle| \Delta \ln \underline{w}_{ict}, \delta_t, \Delta \mathbf{X}_{ict} \right] = 0 \qquad \forall \tau \in \left[\underline{T}, \overline{T} \right]$$

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In words: conditional on FEs, controls, and MW in same ZIP code, unobserved innovations to rent shocks are uncorrelated with past and future values of log MW changes in nearby ZIP codes.

Discussion Identification Assumption

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Is this plausible?

- MW policies are rarely set by considering differential dynamics of the rental housing market within metropolitan areas.
- Furthermore, there is substantial heterogeneity in the housing market across ZIP codes.
- Indirectly test assumption through pre-trends, assuming no anticipatory effects in housing market.

Testing Identification with a Dynamic model

Adding leads and lags of the experienced log MW:

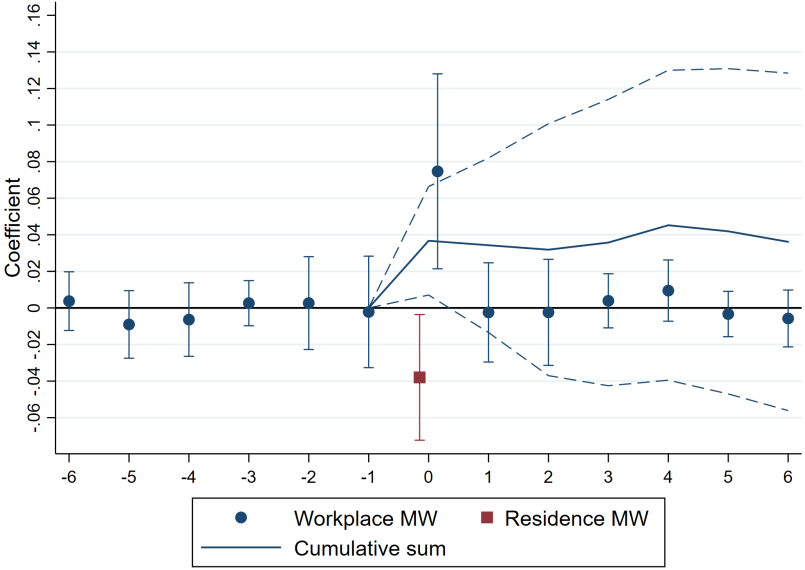
$$\Delta \ln r_{ict} = \delta_t + \sum_{r=-s}^{s} \beta_r \Delta \underline{w}^{\exp}_{ic,t+r} + \gamma \Delta \ln \underline{w}_{ict} + \Delta \mathbf{X}^{'}_{ct} \eta + \Delta \varepsilon_{ict}$$

where $\{\beta_r\}_{r=-s}^{s}$ are the dynamic coefficients.

Analogously, one can add instead the leads and lags of the log residence MW to test the identification assumption of γ.

Results

Static



Coefficient
.16
.14
.12
.1
.08
.06
.04
.02
0
-.02
-.04
-.06
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
Workplace MW
Residence MW
Cumulative sum

Robustness

Heterogeneity

Counterfactuals

Objective

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Take Y_z and H_z as the total nominal income and total housing expenditure at Zip Code z. Let h_z as be the total square footage of rented housing.

Imagine there is a MW change that changes nominal income. We are interested in computing:

$$\rho = \frac{\Delta H_z}{\Delta Y_z} = \frac{h_z^{\text{Post}} r_z^{\text{Post}} - h_z^{\text{Pre}} r_z^{\text{Pre}}}{\Delta Y_z} \tag{1}$$

Counterfactuals - Total rented space

We don't observe h_z^{Pre} and h_z^{Post}. We assume $h_z^{\text{Pre}} = h_z^{\text{Post}} = h_z$ so that:

$$\rho = \frac{h_z^{\text{Post}} r_z^{\text{Post}} - h_z^{\text{Pre}} r_z^{\text{Pre}}}{\Delta Y_z} = h_z \frac{\Delta r_z}{\Delta Y_z}$$

If $\Delta h_i = h_z^{\text{Post}} - h_z^{\text{Pre}} > 0$ then our estimate of ρ is a lower bound.

Counterfactuals - Estimation

We will compute $\rho = h_z \frac{\Delta r_z}{\Delta Y_z}$ in 3 steps:

- **Step 1**: Get an estimate of h_z
- **Step 2**: Use our empirical model to compute Δr_z
- **Step 3**: Use an auxiliary model that maps MW changes to nominal income changes to compute ΔY_z

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Step 1

Haven't found data on h_z. Therefore we do the following:

- In the Zillow data we observe the median rental price per square foot, r_z, but we also observe the median rental price, R_z. Therefore, we can compute $\frac{R_z}{r_z}$ and that gives us the square footage of the median rental at each Zip Code. Call it q_z.
- From the 2019 ACS, we get the number of households that are renting at in each ZIP Code. Call it N_z.

We take that:

$$h_z = q_z N_z$$

Counterfactuals - Estimation

Step 2

Pretend that the federal MW increase to $9.

1. Compute the new binding MW in each Zip Code.
2. Using the commuting shares and the new binding MW's compute the new experienced MW's in each ZIP Code.
3. Compute $\Delta \ln r_z$ using our estimates.
4. Compute $\Delta r_z = \exp(\Delta \ln r_z) r_z^{\text{Pre}}$, where r_z^{Pre} is taken from the Zillow data at December 2019.

Thanks!

Appendix