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

$\Rightarrow$ Housing market.

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$\Rightarrow$ 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 (**Brueckner1987**).
$\rightarrow$ $We are not aware of empirical estimates of that pass-through$!

This paper

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

- Accounting for spatial spillovers, we estimate elasticity of median rents to workplace and residence MWs.
- 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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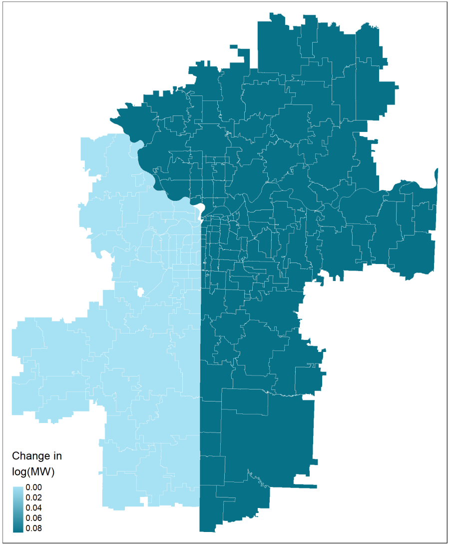
General equilibrium: long term (Not this paper!)

- 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.



A motivating example (Discussion)

A (naive) regression model of changes in rents on changes in MW's will imply that rents can only be affected in the locations where the MW change happened (the Missouri side!).

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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

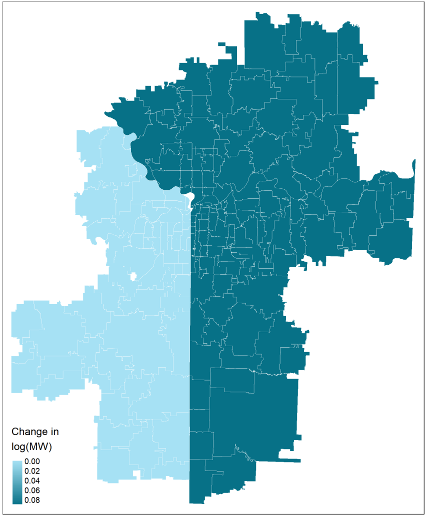
For ZIP code i, and month t we define it as

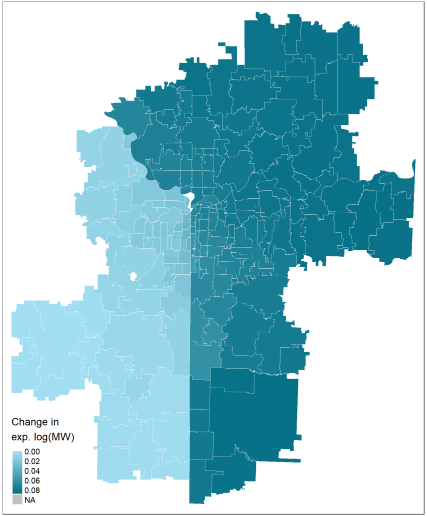
$$\underline{w}_{it}^{\text{exp}} = \sum_{z \in \mathbb{Z}_i} \pi_{iz} \ln \underline{w}_{zt} \ ,$$

where

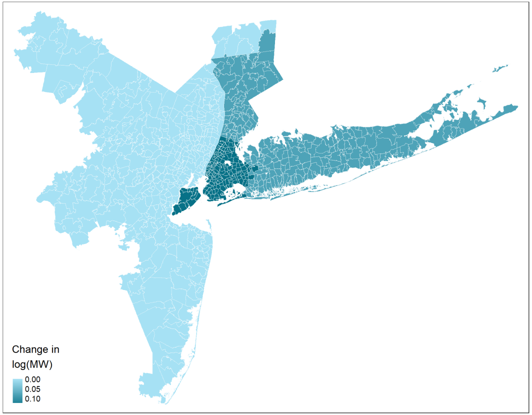
- $\mathbb{Z}_i$ are workplace locations of i's residents, and
- $\pi_{iz} = \frac{L_{iz}}{L_i}$ is the share of i's residents who work in z.

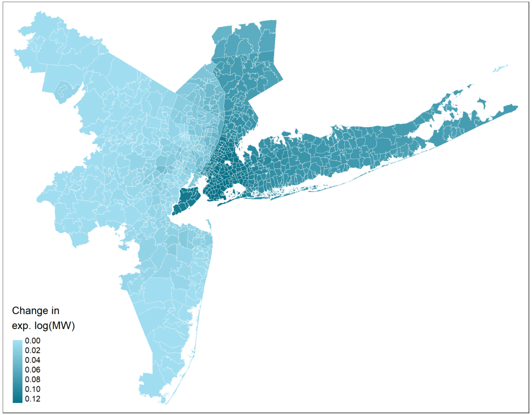
A motivating example (Continuation)



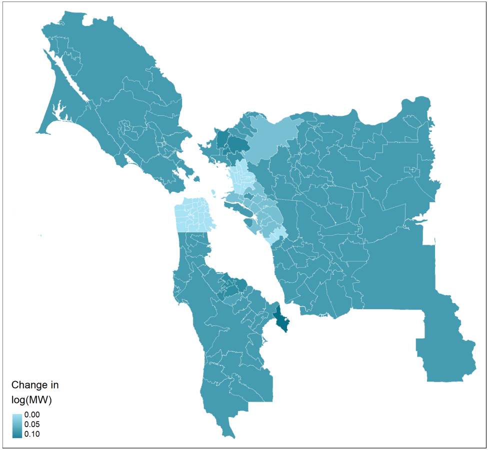


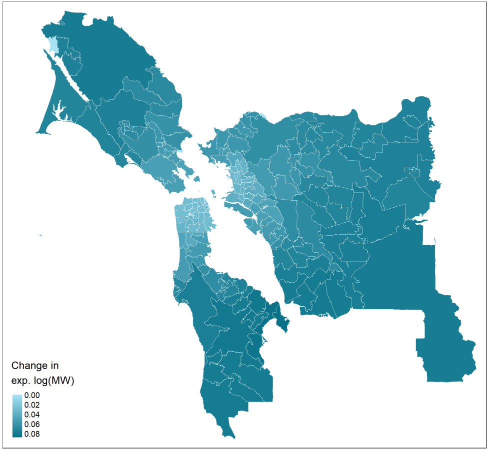
Other examples: New York (MW Changes in January 2019)





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





Outline

Model

Data

Empirical Strategy

Results

Robustness

Heterogeneity

The incidence of counterfactual federal MW change

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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- Use category single-family, condominium, and cooperative houses (SFCC):
  - Most common housing type in the U.S.
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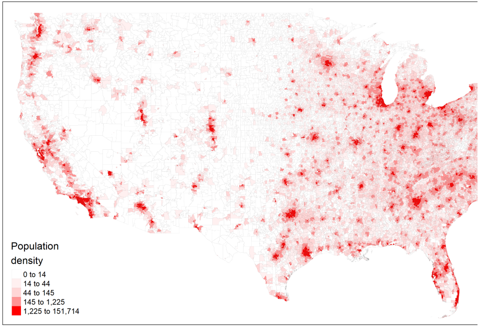
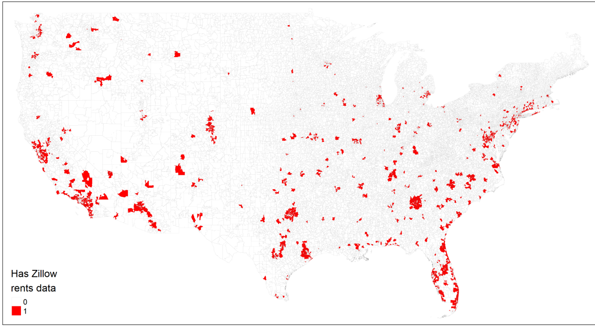
  - Most populated series in Zillow.
- Limitation: Zillow sample is not random.

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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- Define statutory MW in ZIP code as maximum between state and local levels.

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

For causal effect of β we need:

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

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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:

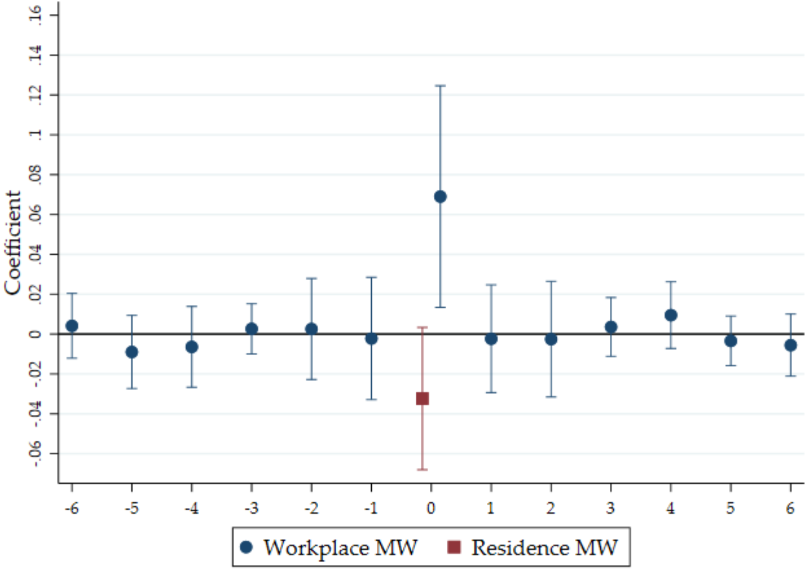
$$\Delta \ln r_{ict} = \delta_t + \sum_{r=-s}^{s} \beta_r \Delta \underline{w}^{\text{exp}}_{ic,t+r} + \gamma \Delta \ln \underline{w}_{ict} + \Delta \mathbf{X}'_{ct} \eta + \Delta \varepsilon_{ict}$$

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

Robustness

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The incidence of counterfactual federal MW change

Overview

Entire commuting structure determines the incidence of MW policies.

- In some ZIP codes both residence and workplace MW increase
- Other nearby ZIP codes are affected only through workplace

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How much out of each extra dollar is captured by landlords?

Pass-through coefficients

Define pass-through coefficients

$$\rho_i := \frac{\Delta H_i}{\Delta Y_i} = \frac{h_i^{\text{Post}} r_i^{\text{Post}} - h_i^{\text{Pre}} r_i^{\text{Pre}}}{\Delta Y_i}$$

where

- h denotes rented space in i (square feet)
- Pre and Post indicate moments before and after the increase

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Change in rented space are unobserved. We assume $h_i^{\text{Pre}} = h_i^{\text{Post}} = h_i$ so

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We construct empirical analogous of h_i, Δr_i and ΔY_i.

Estimates of total rented space

We haven't found data on $\{h_i\}$. Therefore we do the following

- From Zillow get median rental price R_i and median rental price per square foot r_i
- Estimate average square footage $q_i = \frac{R_i}{r_i}$
- Compute number of rented units N_i from ACS 2019

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Our estimates of total rented space in each ZIP code i are

$$\hat{h}_i = q_i N_i$$

Model-based estimates of rent changes

Increase in federal MW to \$9 generates $\{\Delta \ln \hat{\underline{w}}_i\}_{i \in \mathcal{Z}}$

- $\Delta \ln \hat{\underline{w}}_i = 0$ for ZIP codes with binding MWs above \$9

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We proceed as follows

- Estimate $\{\Delta \ln r_i\}$ using our baseline model

$$\Delta \widehat{\ln r_i} = \gamma \Delta \widehat{\ln \underline{w}_i} + \beta \sum_{z \in \mathcal{Z}_i} \pi_{iz} \Delta \widehat{\ln \underline{w}_z}$$

- Using r_i^{Pre} from Zillow as of December 2019, compute

$$\Delta \hat{r}_i = \left(\exp(\Delta \widehat{\ln r_i}) - 1 \right) r_i^{\text{Pre}}$$

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We proceed as follows

- Use elasticity ϵ to get

$$\Delta \ln \hat{Y}_i = \epsilon \sum_{z \in \mathcal{Z}_i} \pi_{iz} \Delta \ln \hat{\underline{w}}_i$$

- Compute $\Delta \hat{Y}_i$ using Y_i^{Pre} as of 2018

$$\Delta \hat{Y}_i = \left(\exp(\Delta \ln \hat{Y}_i) - 1 \right) Y_i^{\text{Pre}}$$

The incidence of MW changes across space

Figure distribution here

Thank You!

Appendix