

# 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:

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⇒ Housing market.

### Theory

A canonical version of the (Muth-Mills) monocentric city model suggests that income increases will pass-through 1:1 to rents (**Brueckner1987**).

## This paper

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

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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.

## This breakfast!

- Intuition and motivating examples
- Model (Not today)
- Data (Shortly)
- Empirical strategy
- Main results (Shortly)
- Robustness (Not today)
- Discussion of potential heterogeneity
- Discussion of potential counterfactuals

## 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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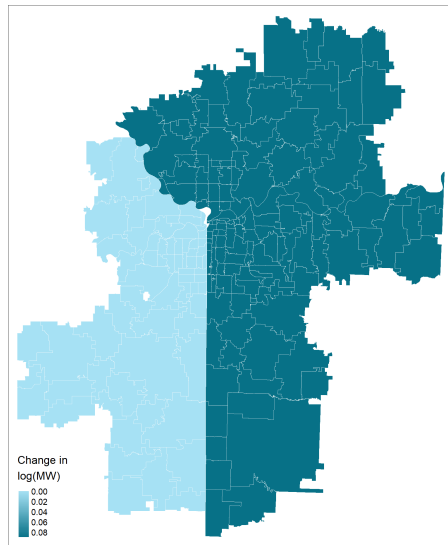
### **General equilibrium: long term** (Not this paper!)

- 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)

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

## A new model-based measure of access to MW's

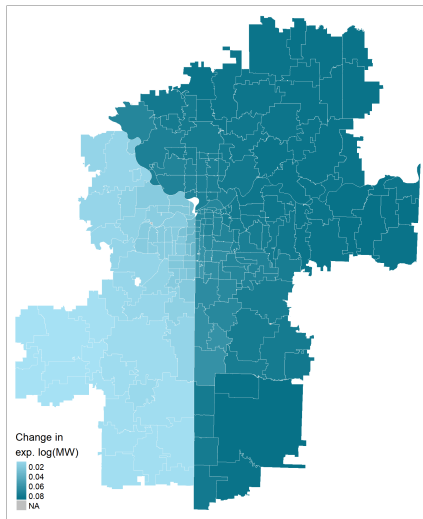
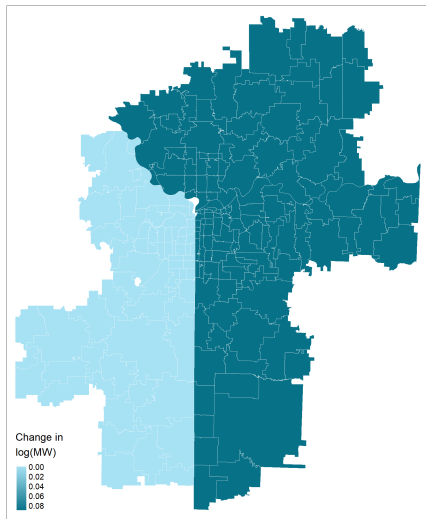
We won't talk about the model today (wait for the lunch in November 2nd!), but with a simple supply and demand model for the rental markets we can represent the elasticity of rents to any *nearby* MW change as a function of the residence location MW and a measure that we define as the **experienced log MW**. For ZIP code  $i$ , and month  $t$  we define it as:

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

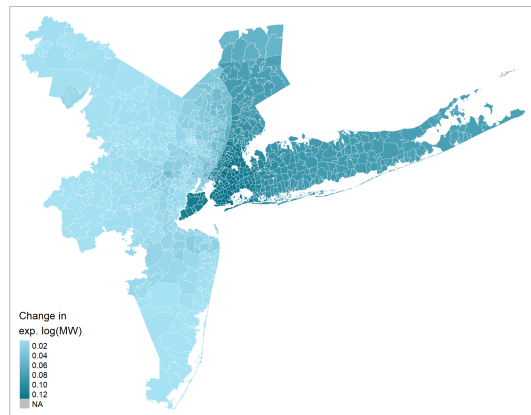
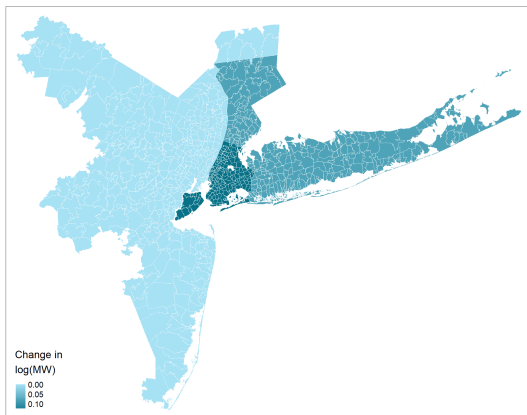
where

- $\mathbb{Z}_i$  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  $z$ .

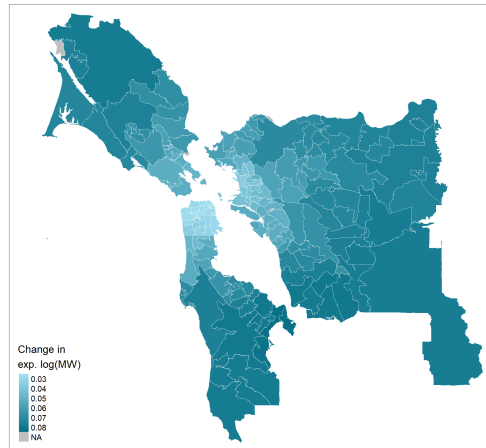
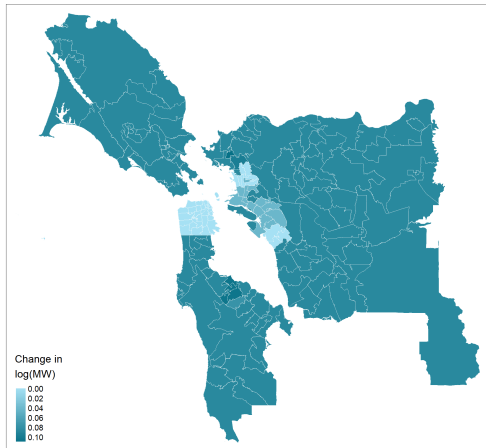
## A motivating example (Continuation)



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



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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.

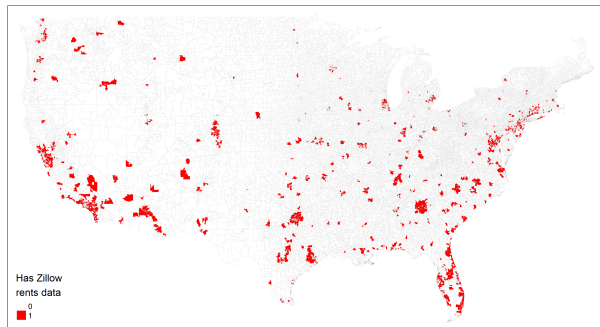
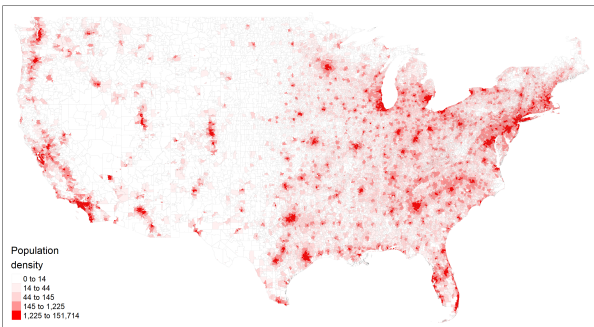
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- Use category single-family, condominium, and cooperative houses (SFCC):
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  - Most populated series in Zillow.
- Limitation: Zillow sample is not random.

## 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.

Distribution of MW 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  $\beta$  we need:

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

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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.

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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:

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

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  $\gamma$ .

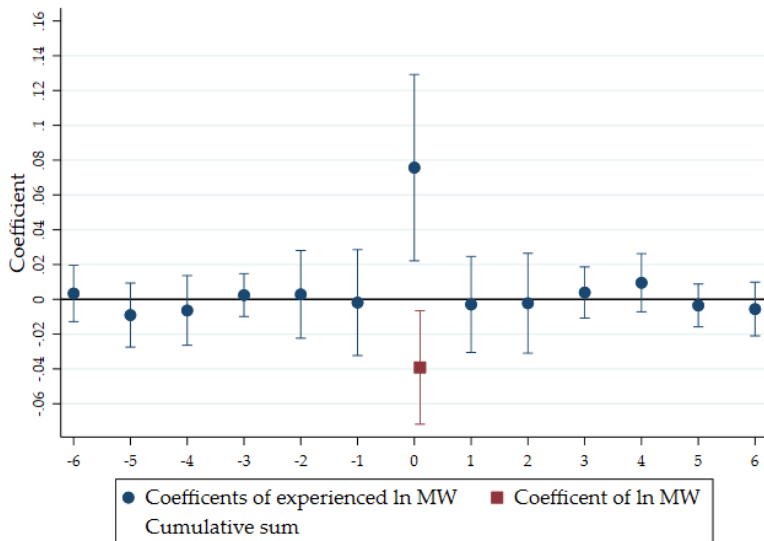


## Results

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└ Results

└ Main Results



## Appendix