Minimum Wage as a Place-Based Policy: Evidence from US Housing Rental Markets

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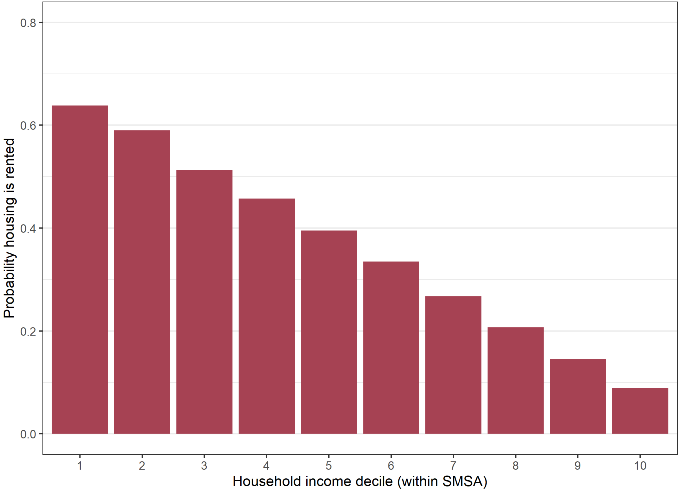
Motivation

Minimum wage policies attempt to improve the livelihoods of low-wage workers.

- Increase wages with small effects on employment (e.g., Cengiz et al. 2019)
- Decrease inequality (Autor, Manning, and Smith 2016) and poverty (Dube 2019)

However, a significant pass-through of MWs to rents may undermine the objectives of the policy.

Low-wage workers are more likely to reside in rentals



Motivation

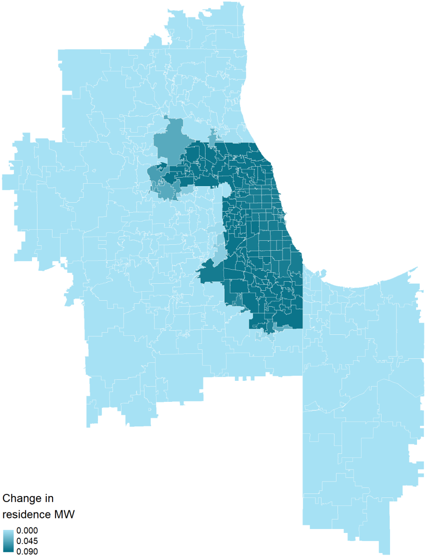
Recently, MW policies in the US have been instituted by sub-national jurisdictions.

- By December 2019: 30 states, 9 counties and 35 cities
- Typically, workers face different MW levels at workplace and residence locations *within cities*

Conceptualize MW levels as *place-based* policies.

- Expect rent effects in locations where workers bound by the policy live
- Long-run: workers sort to locations close to high MW levels (Not this paper!)

A motivating example



Cook County, IL

- Raised local MW from \$12 to \$13 in July 2019.
- State MW is \$8.25 since 2010, and federal MW is \$7.25 since 2009.

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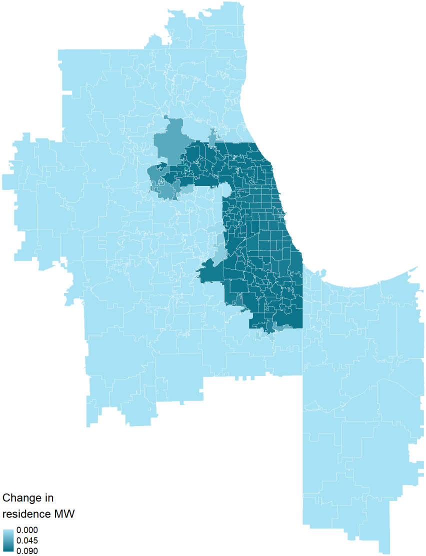


Cook County, IL

- Raised local MW from \$12 to \$13 in July 2019.
- State MW is \$8.25 since 2010, and federal MW is \$7.25 since 2009.
- A model where only same-location MW affects rents would miss likely rents increases outside of Cook County

A novel model-based measure of exposure to minimum wages

For ZIP code i and month t we define the workplace MW as

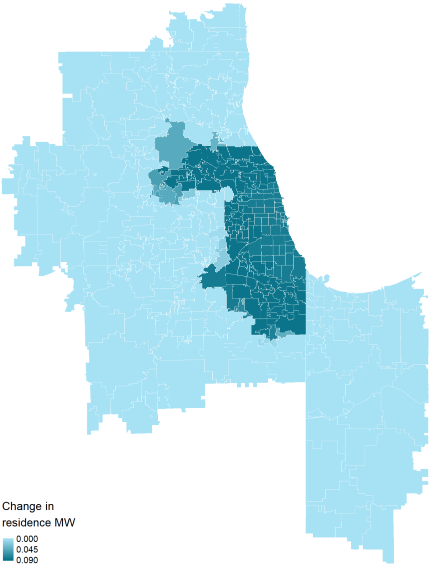
$$\underline{w}_{it}^{\text{wkp}} = \sum_{z \in \mathcal{Z}(i)} \pi_{iz} \ln \underline{W}_{zt} \ ,$$

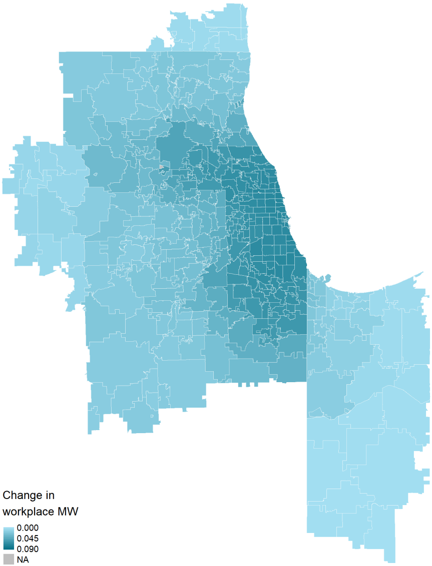
where

- $\underline{W}_{zt}$ is statutory MW in z at time t
- $\mathcal{Z}(i)$ are workplace locations of i's residents
- $\pi_{iz} = L_{iz}/L_i$ is the share of i's residents who work in z

The residence MW is simply

$$\underline{w}_{it}^{\text{res}} = \ln \underline{W}_{it}.$$





NYC | Bay Area | San Diego | Kansas City

This paper

What we do

- Accounting for spatial spillovers, estimate elasticity of rents in the local housing market to workplace MW and residence MW changes
- Estimate share of the extra dollar generated by MW increases pocketed by landlords in each local market

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How we do it

- Propose a novel measure of exposure to MW changes based on commuting shares
- Construct novel dataset of MW policies at ZIP code level
- Exploit high-frequency (month) high-resolution (ZIP code) rents data from Zillow
- Leverage timing and spatial variation in MW changes *within* metropolitan areas

Preview of findings

Main estimation results

- $\uparrow$ 10 percent in workplace MW $\implies$ $\uparrow$ 0.55 percent in rents
- $\uparrow$ 10 percent in residence MW $\implies$ $\downarrow$ 0.21 percent in rents
- $\uparrow$ 10 percent in both measures $\implies$ $\uparrow$ 0.34 percent in rents

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Counterfactual increase in federal MW from \$7.25 to \$9 in highly affected areas

- Rent changes vary between -0.4 to 0.75 percent (median 0.5 percent)
- Share pocketed by landlords is between -15 and 17 cents (median 10 cents)

Outline for Today

Partial Equilibrium Model (intuition)

Data

Empirical Strategy and Results

Counterfactual: A federal MW increase

Concluding remarks

Partial Equilibrium Model (intuition)

Overview

Goals of the model:

- Stylized answer to what is the effect of MW changes on rents
- Motivate and derive a new measure of exposure to MW

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- Motivate and derive a new measure of exposure to MW

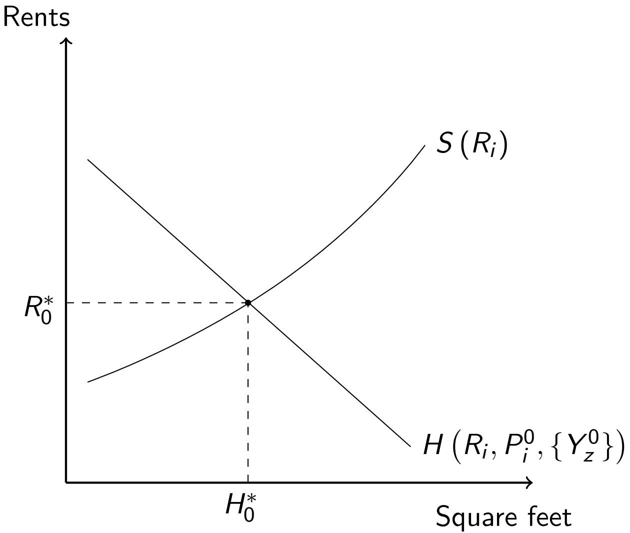
Assumptions:

- A higher MW increases income, which *increases* housing demand
- A higher MW increases non-tradable consumption prices, which *decreases* housing demand
- Static model, so residence and workplace locations of workers are fixed

These assumptions are consistent with the literature.

Comparative statics

1. Equilibrium in ZIP code i



Comparative statics

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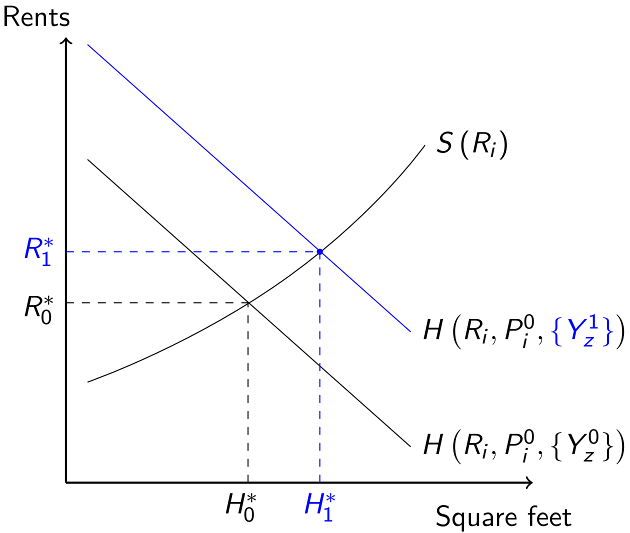

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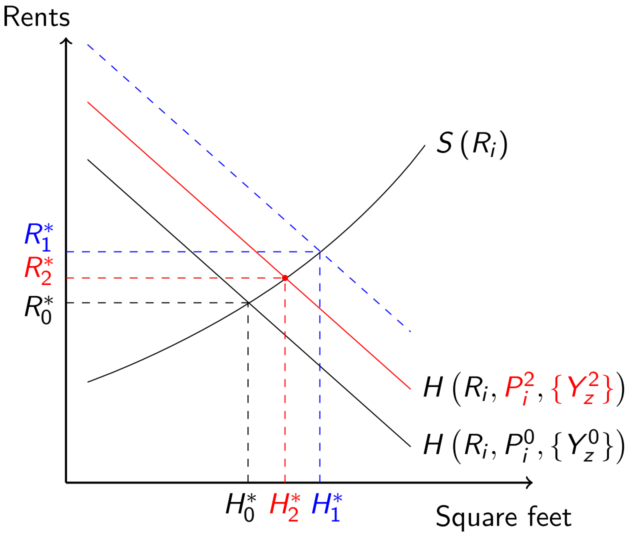

Representation

In this model, assuming homogeneity across workplace locations of

1. elasticity of per-person housing demand to income, and
2. elasticity of income to the MW

we obtain

$$\begin{aligned}\Delta \text{log rents} &= \beta_i \times \Delta \text{workplace MW} \\ &+ \gamma_i \times \Delta \text{residence MW}\end{aligned}$$

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Discussion:

- Assumption (1) would hold for homothetic preferences
- In estimation can allow for heterogeneity as long as not correlated with MW changes

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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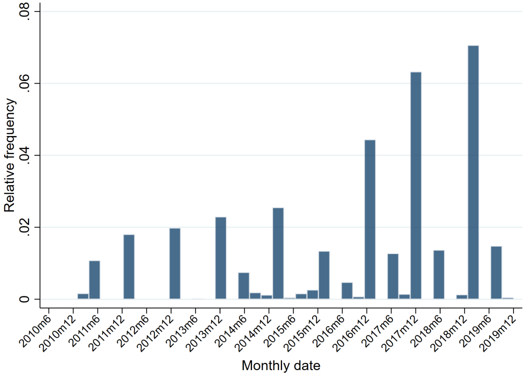
- Provides *median* rents data at ZIP code, county, and state levels at a monthly frequency for several housing categories.
- We use category single-family, condominium, and cooperative houses (SFCC).
  - Most populated series in Zillow
  - We also estimate our models with other housing categories
- Limitation: Zillow sample is not random.

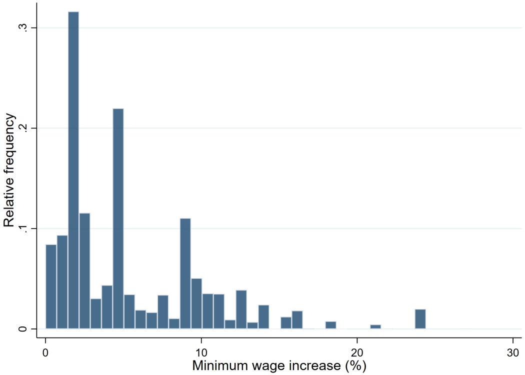
Zillow ZIP Codes and Population Density

The Statutory MW

- Collect MW data at state, county and city levels between Jan 2010 and Dec 2019.
- Spatial match:
  - Assign USPS ZIP codes to census blocks based on blocks' centroids
  - Add matching of places, counties, and states using census crosswalk
- Assign MWs to each block and define statutory MW as maximum between city, county, state, and federal leves.
- Define statutory MW in ZIP code i and month t, $\underline{W}_{it}$, as weighted average of statutory MWs at block, using housing units as weights.

Distribution of (positive) MW changes





US map of MW changes

Constructing the MW measures

Collect data from LEHD Origin-Destination Employment Statistics (LODES) for years 2009–18.

- Origin-destination matrices at block level constructed from tax records

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We observe:

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

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Define the MW measures as

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Empirical Strategy and Results

Empirical model

We estimate versions of the following empirical model:

$$\Delta r_{it} = \delta_t + \beta \Delta \underline{w}_{it}^{\text{wkp}} + \gamma \Delta \underline{w}_{it}^{\text{res}} + \Delta \mathbf{X}_{it}^{'} \eta + \Delta \varepsilon_{it}$$

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For causal effect of β and γ we need:

- (Rank) Independent variation in MW measures after conditioning on controls
- (Parallel trends) Identification assumption:

$$E\left[\begin{pmatrix} \Delta \underline{w}_{is}^{\text{wkp}} \\ \Delta \underline{w}_{is}^{\text{res}} \end{pmatrix} \Delta \varepsilon_{it} \middle| \delta_t, \Delta \mathbf{X}_{it}\right] = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \quad \forall s \in [\underline{T}, \overline{T}]$$

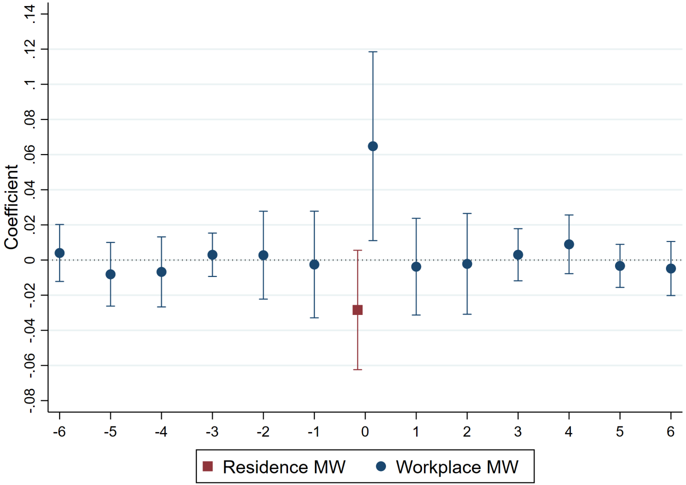
Extend model with leads and lags of the MW measures to test parallel trends.

Main results

	Change wkp. MW $\Delta \underline{w}_{it}^{wkp}$	Change log rents Δr_{it}		
	(1)	(2)	(3)	(4)
Change residence MW $\Delta \underline{w}_{it}^{res}$	0.8705	0.0268		-0.0207
	(0.0298)	(0.0135)		(0.0171)
Change workplace MW $\Delta \underline{w}_{it}^{wkp}$			0.0324	0.0546
			(0.0150)	(0.0281)
Sum of coefficients				0.0339
				(0.0153)
County-quarter economic controls	Yes	Yes	Yes	Yes
P-value equality				0.0938
R-squared	0.9467	0.0209	0.0209	0.0209
Observations	131,383	131,383	131,383	131,383

Note: Standard errors clustered at the state level throughout.

Including leads and lags of workplace MW



Exclude residence MW | Leads and lags of residence MW only | Leads and lags of both

Robustness checks and Other Exercises

Concerns about changes in migration:

- Literature finds small effects along several years (e.g., Pérez Pérez 2021)
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- Re-weight observations to match characteristics of urban ZIP codes

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Other exercises:

- Other housing categories: effects in "Condo/cooperatives" and "Multifamily 5+ units"
- Heterogeneity based on ZIP codes that are likely to have MW *residents* and MW *workers*

Counterfactual: A federal MW increase

Overview

Entire commuting structure determines the incidence of MW policies.

- In some ZIP codes both residence and workplace MW increase
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Consider an increase of the federal MW to $9 in January 2020.

- Changes nominal income $\{\Delta Y_i\}$ and housing expenditure $\{\Delta H_i\}$

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

Define the *share pocketed* as

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

where "Pre" and "Post" indicate moments before and after the increase.

Share pocketed under the model

According to the model,

$$\Delta r_i = \beta \Delta \underline{w}_i^{\text{wkp}} + \gamma \underline{w}_i^{\text{res}}$$

We also define, for $y_i = \ln Y_i$,

$$\Delta y_i = \varepsilon \Delta \underline{w}_i^{\text{wkp}}$$

We estimate ε using IRS data. Estimation results

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Assuming $H_i^{\text{Pre}} = H_i^{\text{Post}} = H_i$, the share pocketed becomes

$$\rho_i = \alpha_i \left[\frac{\exp\left(\beta \Delta \underline{w}_i^{\text{wkp}} + \gamma \Delta \underline{w}_i^{\text{res}}\right) - 1}{\exp\left(\varepsilon \Delta \underline{w}_i^{\text{wkp}}\right) - 1} \right]$$

where $\alpha_i = (H_i R_i) \,/\, Y_i$ is the share of i's expenditure in housing.
(If $\Delta H_i > 0$ our estimates are a lower bound.)

Share pocketed under the model

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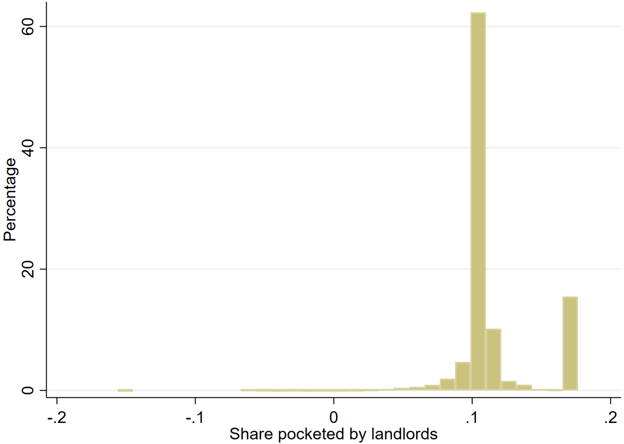
Use estimates to compute $\{\rho_i\}$ for urban ZIP codes are located in affected CBSAs.

The distribution of the share pocketed by landlords



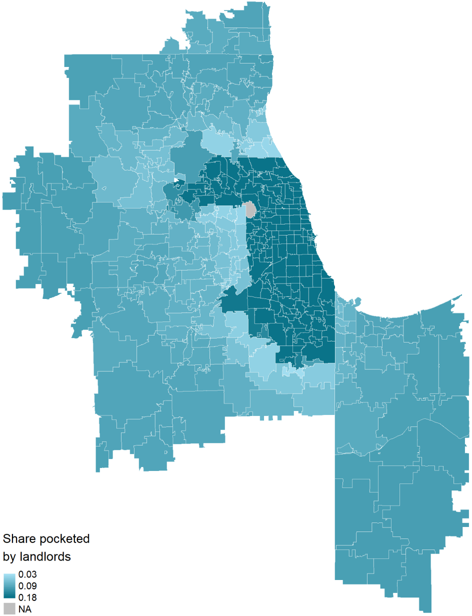
Notes: Share estimated using parameters $\beta = 0.0546$, $\gamma = -0.0207$, $\varepsilon = 0.1083$, and $\alpha = 0.35$. We include 6,952 ZIP codes located in CBSAs where average estimated income increase is of at least 0.1%. The residence MW did not change for 1,070 ZIP codes in this sample.

Share pocketed in Chicago CBSA

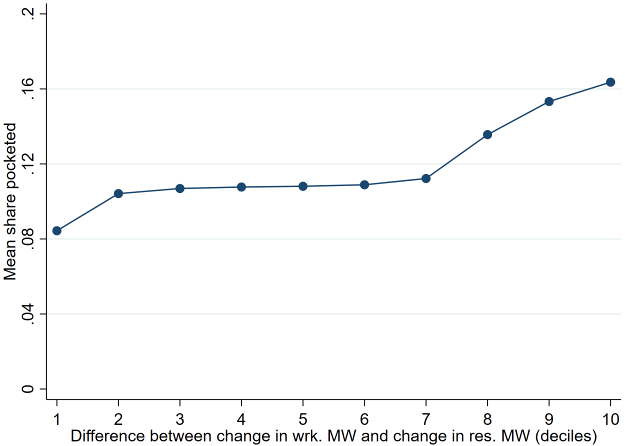
Share pocketed is larger inside of Cook County.

Mapping intermediate computations:

- Estimated changes in MW measures here
- Estimated changes in rents and income here



The incidence of MW changes according to intensity of treatment



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Concluding remarks

Conclusions

- When studying effects of place-based policies on housing markets one must account for divergence between workplace and residence locations
- In the case of the MW, hikes in workplace locations *increase* rents whereas hikes in residence locations *decrease* rents
- Even with a two-parameter model we are able to describe and predict rich spatial patterns in rent changes
- Landlords pocket a non-negligible fraction of the income increase generated by the MW
- Ignoring the housing market will lead to an overstatement of the positive effects of MW policies

Thank You!

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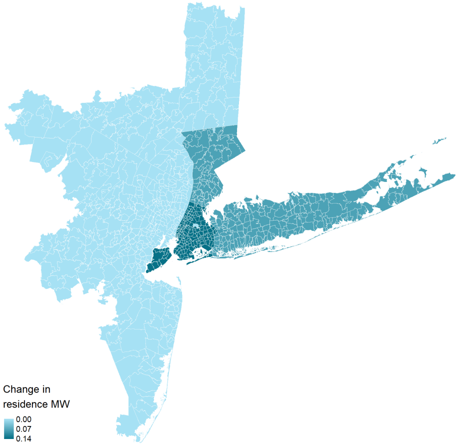
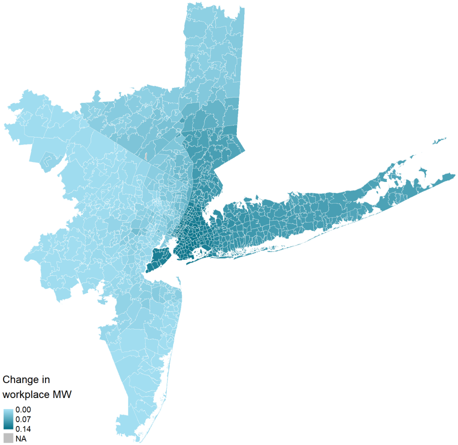
Appendix

New York (MW changes in January 2019)





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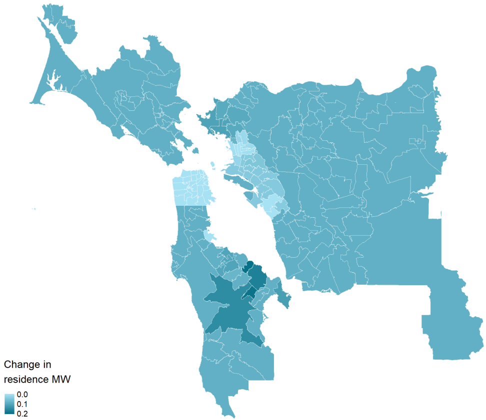
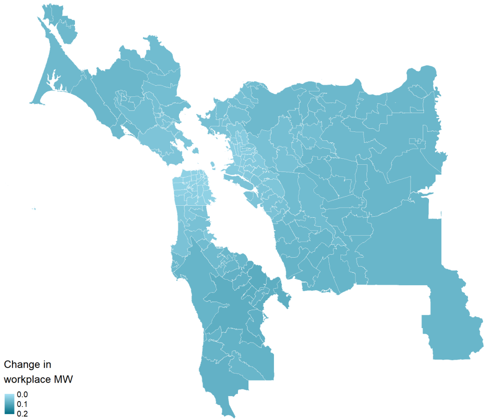
Bay area (MW changes in January 2019)





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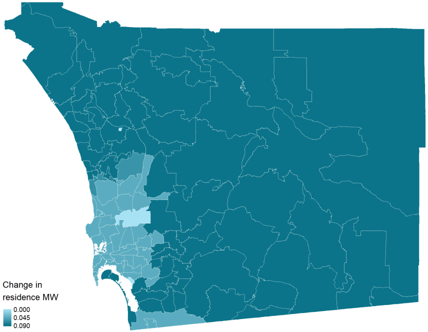
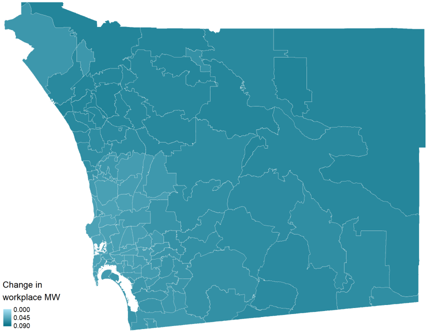
San Diego (MW changes in January 2019)





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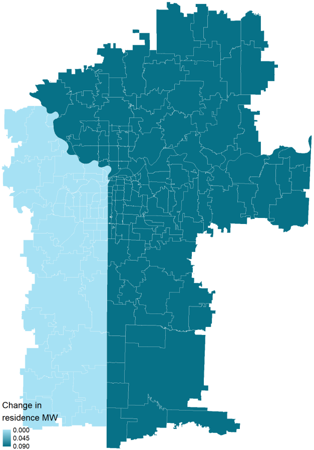
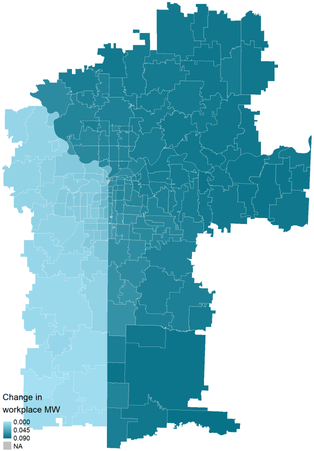
Kansas City (MW changes in January 2019)





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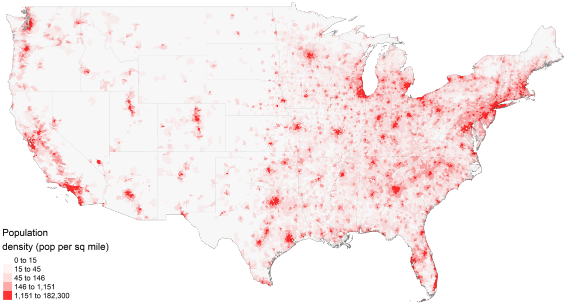
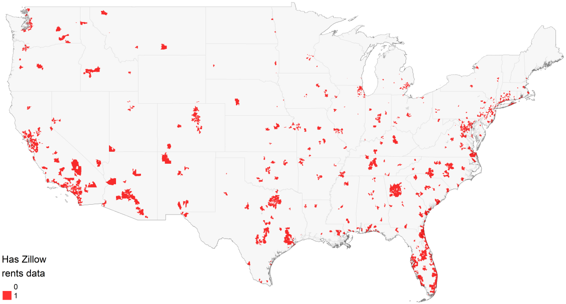
Comparison between Zillow Sample and Population Density





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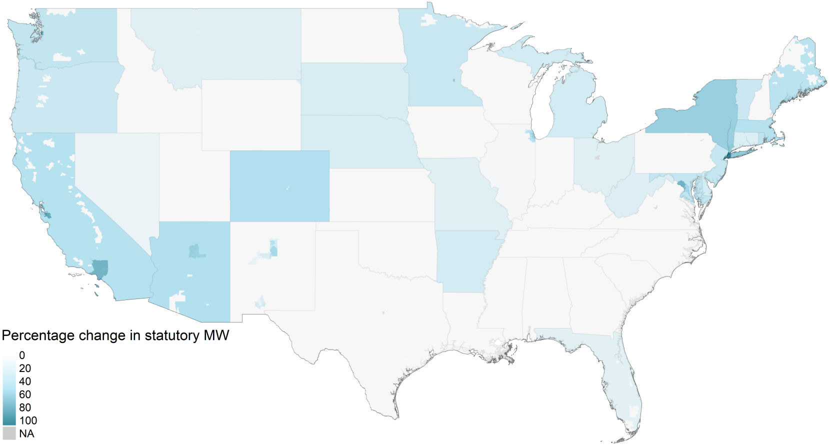
MW changes between Jan 2010 and Dec 2019, mainland US



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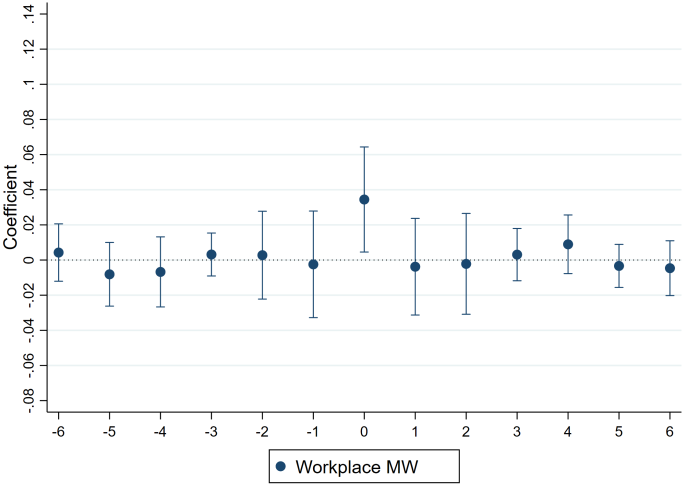
Excluding residence MW



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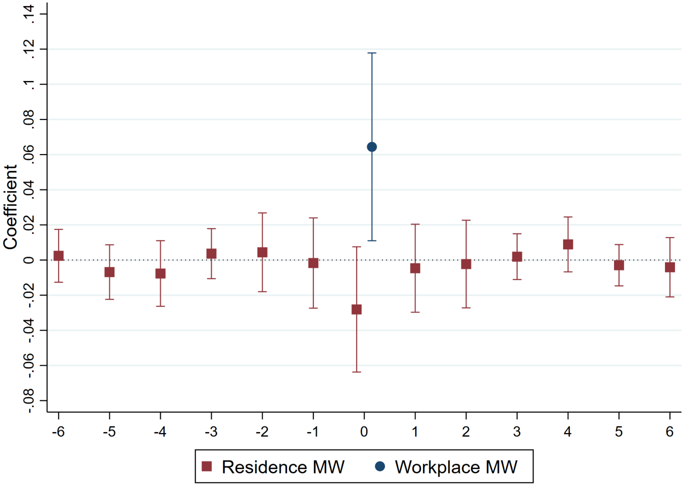
Including leads and lags of residence MW



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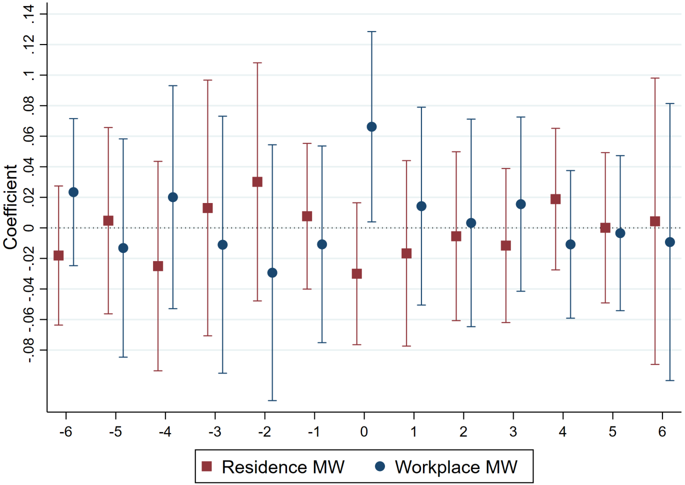
Including leads and lags of both MW measures



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Sample selection concerns

	Change log rents Δr_{it}					
	Baseline (1)	Baseline Reweighted (2)	Fully-balanced (3)	Fully-balanced Reweighted (4)	Unbalanced (5)	Unbalanced Reweighted (6)
Change residence MW $\Delta \underline{w}_{it}^{\text{res}}$	-0.0207	-0.0186	-0.0201	-0.0223	-0.0254	-0.0168
	(0.0171)	(0.0309)	(0.0200)	(0.0307)	(0.0210)	(0.0204)
Change workplace MW $\Delta \underline{w}_{it}^{\text{wkp}}$	0.0546	0.0581	0.0682	0.0868	0.0471	0.0393
	(0.0281)	(0.0427)	(0.0306)	(0.0389)	(0.0309)	(0.0369)
P-value equality	0.0938	0.2863	0.0792	0.1101	0.1559	0.3146
R-squared	0.0209	0.0185	0.0216	0.0180	0.0160	0.0127
Observations	131,383	130,533	78,912	78,381	193,292	192,177

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Estimates of the effect of the MW on total wages in a ZIP code

	Log total wages				Log dividends
	(1)	(2)	(3)	(4)	(5)
Workplace MW	0.1488	0.1112	0.1083	0.1310	0.0262
	(0.0704)	(0.0405)	(0.0390)	(0.0917)	(0.0841)
Sample	All	All	All	Baseline	All
Economic controls	No	Yes	Yes	Yes	Yes
CBSA $\times$ year FE	No	No	Yes	Yes	Yes
Within R-squared	0.0165	0.1395	0.0266	0.0376	0.0018
Observations	274,271	247,962	247,852	12,943	235,193

Notes: unit of observation is ZIP code by year pairs. All regressions include ZIP code FE and year FE. Workplace MW measure is yearly average of monthly 2017 variable.

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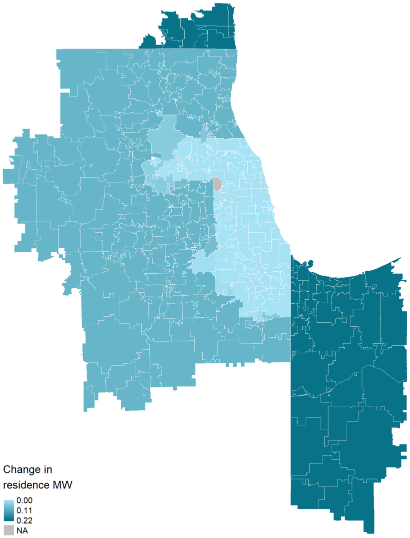
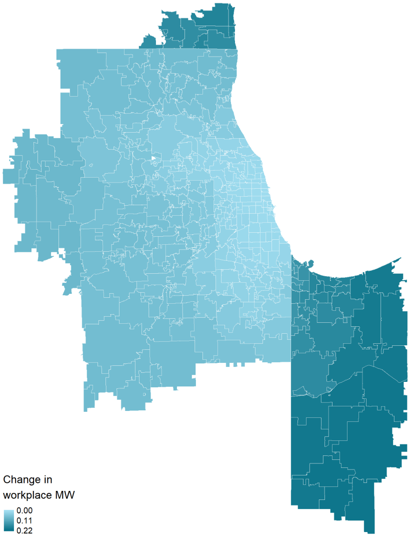
Residence MW



Workplace MW



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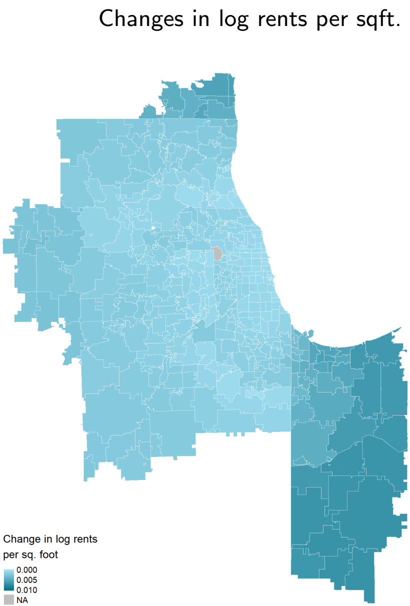
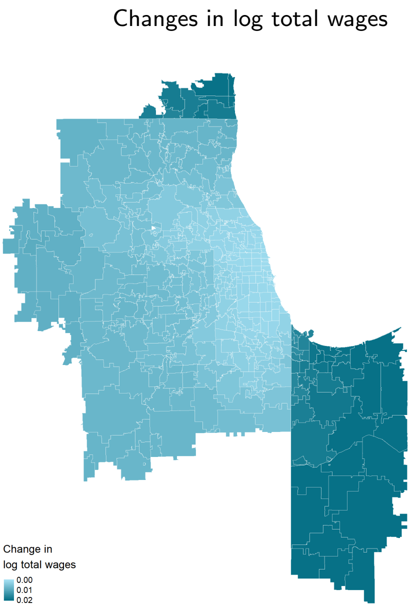

Changes in log rents per sqft.
Change in log rents
per sq. foot
0.000
0.005
0.010
NA


Changes in log total wages
Change in
log total wages
0.00
0.01
0.02

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