

Do Minimum Wages Increase Rents?

Evidence from US ZIP Codes Using High-Frequency Data

Gabriele Borg Diego Gentile Passaro Santiago Hermo

Brown University

February 23, 2021

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:

⇒ Housing market.

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:

⇒ Housing market.

Because

- people tend to work and reside in different locations; and
- MW levels tend to vary within metropolitan areas;

accurate welfare analysis of MW increases requires understanding the consequences of the spatial re-distribution of income they induce.

This paper

We investigate the effect of MW policies on rents between Jan 2010 and Dec 2019:

- Estimate elasticity of median rents to workplace and residence MWs;
- Estimate pass-through of MW increases to rents.

This paper

We investigate the effect of MW policies on rents between Jan 2010 and Dec 2019:

- Estimate elasticity of median rents to workplace and residence MWs;
- Estimate pass-through of MW increases to rents.

To do so, we:

- Exploit high-frequency rents data from Zillow at a fine geography (ZIP code);
- Propose a novel measure of exposure to MW changes based on commuting shares;
- Leverage variation in MW levels *within* metropolitan areas to estimate effect of workplace and residence MWs changes.

Preview of Findings

We find that:

- The elasticity of rents to workplace MW is 0.072–0.108;
- If residence MW also increases, the elasticity is 0.034–0.061;
- Failing to account for commuting patterns results in an elasticity of 0.026–0.058 *only at residence*;
- The pass-through of MW to rents is at least 22%.

Preview of Findings

We find that:

- The elasticity of rents to workplace MW is 0.072–0.108;
- If residence MW also increases, the elasticity is 0.034–0.061;
- Failing to account for commuting patterns results in an elasticity of 0.026–0.058 *only at residence*;
- The pass-through of MW to rents is at least 22%.

Overall, our results highlight the importance of accounting for variation of MWs within metropolitan areas and commuting patterns of workers when evaluating MW policies.

Outline

A Partial Equilibrium Model of the Rental Market

Data and Sample

Empirical Strategy

Results

Concluding Remarks

A Partial Equilibrium Model of the Rental Market

Overview

Goals of the model:

- Motivate a new MW measure: the experienced MW.
- Motivate our empirical strategy: use commuting patterns to account for spillovers of MW policies.

Overview

Goals of the model:

- Motivate a new MW measure: the experienced MW.
- Motivate our empirical strategy: use commuting patterns to account for spillovers of MW policies.

The model is *not* intended to:

- Describe within-city residential sorting or local goods markets.
- Perform welfare analysis of MW policies.

Simple Illustration

No commuting across ZIP codes:

ZIP code A	ZIP code B
MW stays constant	MW \uparrow 10%

Simple Illustration

No commuting across ZIP codes:

ZIP code A	ZIP code B
MW stays constant	MW \uparrow 10%
Income stays constant	Income \uparrow 1%

Simple Illustration

No commuting across ZIP codes:

ZIP code A	ZIP code B
MW stays constant	MW \uparrow 10%
Income stays constant	Income \uparrow 1%
Rents stay constant	Rents \uparrow 0.5%

Simple Illustration

No commuting across ZIP codes:

ZIP code A	ZIP code B
MW stays constant	MW \uparrow 10%
Income stays constant	Income \uparrow 1%
Rents stay constant	Rents \uparrow 0.5%

All residents of A work in B and vice-versa:

ZIP code A	ZIP code B
MW stays constant	MW \uparrow 10%

Simple Illustration

No commuting across ZIP codes:

ZIP code A	ZIP code B
MW stays constant	MW \uparrow 10%
Income stays constant	Income \uparrow 1%
Rents stay constant	Rents \uparrow 0.5%

All residents of A work in B and vice-versa:

ZIP code A	ZIP code B
MW stays constant	MW \uparrow 10%
Income \uparrow 2%	Income \downarrow 1%

Simple Illustration

No commuting across ZIP codes:

ZIP code A	ZIP code B
MW stays constant	MW \uparrow 10%
Income stays constant	Income \uparrow 1%
Rents stay constant	Rents \uparrow 0.5%

All residents of A work in B and vice-versa:

ZIP code A	ZIP code B
MW stays constant	MW \uparrow 10%
Income \uparrow 2%	Income \downarrow 1%
Rents \uparrow 1%	Rents \downarrow 0.5%

Set-up

- \mathbb{Z} : set of ZIP codes, indexed by i (residence) and z (workplace).

Set-up

- \mathbb{Z} : set of ZIP codes, indexed by i (residence) and z (workplace).
- L_{iz} : measure of workers who reside in i and work in z .
 - Total measure of workers $\mathcal{L} = \sum_{i \in \mathbb{Z}} \sum_{z \in \mathbb{Z}} L_{iz}$ is assumed exogenous.

Set-up

- \mathbb{Z} : set of ZIP codes, indexed by i (residence) and z (workplace).
- L_{iz} : measure of workers who reside in i and work in z .
 - Total measure of workers $\mathcal{L} = \sum_{i \in \mathbb{Z}} \sum_{z \in \mathbb{Z}} L_{iz}$ is assumed exogenous.
- $y_{iz} = y_{iz}(\underline{w}_i, \underline{w}_z)$: disposable income, where:
 - \underline{w}_i and \underline{w}_z are residence and workplace MWs.

Set-up

- \mathbb{Z} : set of ZIP codes, indexed by i (residence) and z (workplace).
- L_{iz} : measure of workers who reside in i and work in z .
 - Total measure of workers $\mathcal{L} = \sum_{i \in \mathbb{Z}} \sum_{z \in \mathbb{Z}} L_{iz}$ is assumed exogenous.
- $y_{iz} = y_{iz}(\underline{w}_i, \underline{w}_z)$: disposable income, where:
 - \underline{w}_i and \underline{w}_z are residence and workplace MWs.
- $H_{iz}(r_i, y_{iz})$: housing demand, where r_i represents housing rents.

Set-up

- \mathbb{Z} : set of ZIP codes, indexed by i (residence) and z (workplace).
- L_{iz} : measure of workers who reside in i and work in z .
 - Total measure of workers $\mathcal{L} = \sum_{i \in \mathbb{Z}} \sum_{z \in \mathbb{Z}} L_{iz}$ is assumed exogenous.
- $y_{iz} = y_{iz}(\underline{w}_i, \underline{w}_z)$: disposable income, where:
 - \underline{w}_i and \underline{w}_z are residence and workplace MWs.
- $H_{iz}(r_i, y_{iz})$: housing demand, where r_i represents housing rents.
- $D_i(r_i)$: housing supply.

Assumptions

Disposable income y_{iz} :

- decreasing in residence MW, $\frac{dy_{iz}}{d\underline{w}_i} < 0$.
- increasing in workplace MW, $\frac{dy_{iz}}{d\underline{w}_z} > 0$.

Assumptions

Disposable income y_{iz} :

- decreasing in residence MW, $\frac{dy_{iz}}{d\underline{w}_i} < 0$.
- increasing in workplace MW, $\frac{dy_{iz}}{d\underline{w}_z} > 0$.

Housing demand $H_{iz}(r_i, y_{iz})$:

- decreasing in rents, $\frac{dH_{iz}}{dr_i} < 0$;
- increasing in disposable income, $\frac{dH_{iz}}{dy_{iz}} > 0$.

Assumptions

Disposable income y_{iz} :

- decreasing in residence MW, $\frac{dy_{iz}}{d\underline{w}_i} < 0$.
- increasing in workplace MW, $\frac{dy_{iz}}{d\underline{w}_z} > 0$.

Housing demand $H_{iz}(r_i, y_{iz})$:

- decreasing in rents, $\frac{dH_{iz}}{dr_i} < 0$;
- increasing in disposable income, $\frac{dH_{iz}}{dy_{iz}} > 0$.

Housing supply:

- $D_i(r_i)$ is increasing in rents, $\frac{dD_i}{dr_i} > 0$.

Equilibrium

The rental market of ZIP code i is in equilibrium if

$$\sum_{z \in \mathbb{Z}} L_{iz} H_{iz}(r_i, y_{iz}) = D_i(r_i).$$

We denote equilibrium rents as $r_i^* = f(\{\underline{w}_j\}_{j \in \mathbb{Z}})$.

Equilibrium

The rental market of ZIP code i is in equilibrium if

$$\sum_{z \in \mathbb{Z}} L_{iz} H_{iz}(r_i, y_{iz}) = D_i(r_i).$$

We denote equilibrium rents as $r_i^* = f(\{\underline{w}_j\}_{j \in \mathbb{Z}})$.

We are interested in the effects of MW policies on rents.

- What are the consequences of not accounting for both residence and workplace MWs?
- Under what conditions one can reduce the dimensionality in the rents function?

The Differential Effect of Residence and Workplace MWs

Proposition 1: *Consider a new MW policy. Under the assumptions of*

- *fixed distribution of workers across residence and workplace locations;*

The Differential Effect of Residence and Workplace MWs

Proposition 1: *Consider a new MW policy. Under the assumptions of*

- *fixed distribution of workers across residence and workplace locations;*
- *disposable income is increasing in workplace MW and decreasing in residence MW;*

The Differential Effect of Residence and Workplace MWs

Proposition 1: *Consider a new MW policy. Under the assumptions of*

- *fixed distribution of workers across residence and workplace locations;*
- *disposable income is increasing in workplace MW and decreasing in residence MW;*

*we have that workplace-MW hikes **increase** rents, and residence-MW hikes, **conditional** on workplace MWs, **decrease** rents.*

The Differential Effect of Residence and Workplace MWs

Proposition 1: *Consider a new MW policy. Under the assumptions of*

- *fixed distribution of workers across residence and workplace locations;*
- *disposable income is increasing in workplace MW and decreasing in residence MW;*

*we have that workplace-MW hikes **increase** rents, and residence-MW hikes, **conditional** on workplace MWs, **decrease** rents.*

Furthermore, assuming that

- *elasticities of rents to income and of income to MWs do not vary by workplace;*

The Differential Effect of Residence and Workplace MWs

Proposition 1: *Consider a new MW policy. Under the assumptions of*

- *fixed distribution of workers across residence and workplace locations;*
- *disposable income is increasing in workplace MW and decreasing in residence MW;*

*we have that workplace-MW hikes **increase** rents, and residence-MW hikes, **conditional** on workplace MWs, **decrease** rents.*

Furthermore, assuming that

- *elasticities of rents to income and of income to MWs do not vary by workplace;*

*we can write the change in **log rents** as a function of the change in two MW-based measures: **experienced log MW** and **statutory log MW**.*

Proof of Proposition 1

First part of the proposition can be shown applying implicit function theorem.

[Details](#)

Proof of Proposition 1

First part of the proposition can be shown applying implicit function theorem.

[Details](#)

As for the second part, we can write

$$d \ln r_i = \underbrace{\frac{\xi_i^y \epsilon_i^z}{\eta_i - \sum_z \pi_{iz} \xi_{iz}^r}}_{\beta_i > 0} \underbrace{\sum_z \pi_{iz} d \ln \underline{w}_z}_{\text{Exp. log MW at residence}} + \underbrace{\frac{\xi_i^y \epsilon_i^i}{\eta_i - \sum_z \pi_{iz} \xi_{iz}^r}}_{\gamma_i < 0} \underbrace{d \ln \underline{w}_i}_{\text{Stat. log MW at residence}}$$

where

- π_{iz} : share of i 's residents working in z ;
- ξ_{iz}^r and ξ_i^y : elasticities of H_{iz} wrt r and y (ξ_i^y assumed constant over z);
- ϵ_i^i and ϵ_i^z : elasticities of y_{iz} wrt \underline{w}_i and \underline{w}_z (both assumed constant over z);
- η_i : elasticity of *housing supply*.

Implications of the Model

Per equation above, we are interested in the parameters

$$\beta_i = \frac{\xi_i^y \epsilon_i^z}{\eta_i - \sum_z \pi_{iz} \xi_{iz}^r} > 0 \qquad \gamma_i = \frac{\xi_i^y \epsilon_i^i}{\eta_i - \sum_z \pi_{iz} \xi_{iz}^r} < 0.$$

Implications of the Model

Per equation above, we are interested in the parameters

$$\beta_i = \frac{\xi_i^y \epsilon_i^z}{\eta_i - \sum_z \pi_{iz} \xi_{iz}^r} > 0 \quad \gamma_i = \frac{\xi_i^y \epsilon_i^i}{\eta_i - \sum_z \pi_{iz} \xi_{iz}^r} < 0.$$

Imagine an econometrician who omits one of the measures in the above model:

- It can be shown that the resulting elasticity will be between γ_i and β_i .

Discussion

- Including both the statutory and experienced log MW should allow estimation of the differential effect of MWs on rents from workplace and residence changes.
 - Assumption of fixed π_{iz} shares appears plausible in short-run.
(Monte, Redding, and Rossi-Hansberg 2018; Cengiz et al. 2019; Pérez Pérez 2020)
 - Assumption that local MWs decrease disposable income is consistent with literature on price effects of MWs.
(Allegretto and Reich 2018; Leung 2020)
- Can test the model's rationale by including only the statutory or experienced log MW in empirical models and comparing with main estimates.

Data and Sample

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.

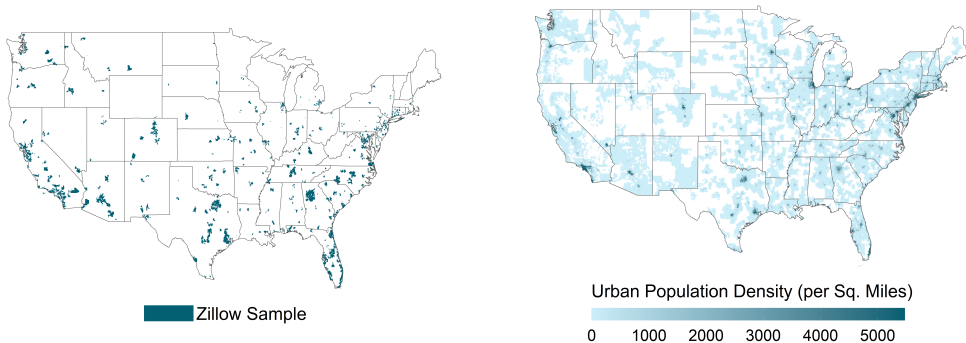
Zillow Data

- 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.
- Use category single-family, condominium, and cooperative houses (SFCC):
 - Most common housing type in the U.S.
 - Most populated series in Zillow.

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

Comparison between Zillow Sample and Population Density



Notes: Left panel shows ZIP codes available in Zillow data. Right panel shows the urban population density for the top 100 metropolitan areas in the U.S. from the 2008-2011 ACS (winsorized at the 99th percentile).

The Statutory MW

- Collect MW data at state, county and city levels between Jan 2010 and Dec 2019.
- Assign those data to ZIP codes.
- Define statutory MW in ZIP code as maximum between state and local levels.

The Statutory MW

- Collect MW data at state, county and city levels between Jan 2010 and Dec 2019.
- 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.
- Analogously, number of workers younger than 29 and earning less than \$1,251.

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.
- Analogously, number of workers younger than 29 and earning less than \$1,251.

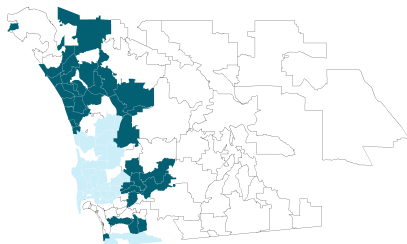
Define **experienced log MW** in ZIP code i month t as

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

where

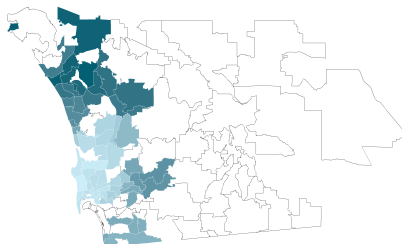
- \mathbb{Z}_i are workplace locations of i 's residents, and
- $\pi_{iz} = \frac{L_{iz}}{L_i}$ is the share of i 's residents who work in z .

The California MW Increase of January 2019 in San Diego



6-month diff. in log MW (x100)

5 6 7 8



6-month diff. in log MW (x100)

5 6 7

Other Data Sources and Sample Selection

Other data sources:

- Economic controls from the Quarterly Census of Employment and Wages (QCEW).

Other Data Sources and Sample Selection

Other data sources:

- Economic controls from the Quarterly Census of Employment and Wages (QCEW).

ZIP codes enter Zillow data in different months.

- To account for composition changes in the sample, we use ZIP codes with valid rents data as of July 2015 as baseline. (1,305 ZIP codes, 4,224 events.)

We conduct several exercises changing the sample, and find consistent results.

Baseline Sample: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Statutory log MW	155,295	2.08	0.13	1.98	2.77
Experienced log MW	155,295	2.07	0.13	1.72	2.70
Median rent psqft. SFCC	113,375	1.27	0.83	0.47	7.25
Median rent SFCC	125,644	1,651.10	702.99	595.00	6,595.00
Avg. wage Fin. activities	151,032	1,561.71	961.88	0.00	9,557.00
Employment Fin. activities	151,032	59,595.23	75,840.23	0.00	397,839.00
Estab. count Fin. activities	151,032	5,105.58	5,201.89	31.00	30,405.00

Notes: The table shows summary statistics of some variables in our baseline estimating sample, which includes 1,305 ZIP codes and runs from January 2010 to December 2019.

Empirical Strategy

Static (statutory only) model

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

$$\Delta \ln r_{ict} = \tilde{\delta}_t + \tilde{\beta} \Delta \ln \underline{w}_{ict} + \Delta \mathbf{X}'_{ict} \tilde{\eta} + \Delta \tilde{\varepsilon}_{ict},$$

where

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

Static (statutory only) model: Identification assumption

For causal effect of the MW need conditional *strict exogeneity*.

Formally, for every period t need to assume:

$$E \left[\Delta \tilde{\varepsilon}_{ict} \Delta \ln \underline{w}_{ic\tau} \middle| \tilde{\delta}_t, \Delta \mathbf{X}_{ict} \right] = 0 \quad \forall \tau \in [\underline{T}, \overline{T}] .$$

Static (statutory only) model: Identification assumption

For causal effect of the MW need conditional *strict exogeneity*.

Formally, for every period t need to assume:

$$E \left[\Delta \tilde{\varepsilon}_{ict} \Delta \ln \underline{w}_{ic\tau} \middle| \tilde{\delta}_t, \Delta \mathbf{X}_{ict} \right] = 0 \quad \forall \tau \in [\underline{T}, \overline{T}] .$$

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

Static Model

Now add experienced MW:

$$\Delta \ln r_{ict} = \delta_t + \beta \Delta \underline{w}_{ict}^{\text{exp}} + \gamma \Delta \ln \underline{w}_{ict} + \Delta \mathbf{X}'_{ict} \eta + \Delta \varepsilon_{ict},$$

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

Static Model

Now add experienced MW:

$$\Delta \ln r_{ict} = \delta_t + \beta \Delta \underline{w}_{ict}^{\text{exp}} + \gamma \Delta \ln \underline{w}_{ict} + \Delta \mathbf{X}'_{ict} \eta + \Delta \varepsilon_{ict},$$

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:

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

Static Model

Now add experienced MW:

$$\Delta \ln r_{ict} = \delta_t + \beta \Delta \underline{w}_{ict}^{\text{exp}} + \gamma \Delta \ln \underline{w}_{ict} + \Delta \mathbf{X}_{ict}' \eta + \Delta \varepsilon_{ict},$$

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:

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

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.

Static Model: Identification Assumption

Thus, for causal effect of β we need:

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

Analogously, for causal effect of γ we need:

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

Static Model: Identification Assumption

Thus, for causal effect of β we need:

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

Analogously, for causal effect of γ we need:

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

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.

Main threats to Identification

- State of the economy correlated both with rents and MW changes at same or nearby ZIP codes.
 - ⇒ Control for employment, average wages, and establishment count of sectors with almost no MW workers: *Financial, IT, and Professional and Business Services*.

Main threats to Identification

- State of the economy correlated both with rents and MW changes at same or nearby ZIP codes.
 - ⇒ Control for employment, average wages, and establishment count of sectors with almost no MW workers: *Financial, IT, and Professional and Business Services*.
- Anticipatory effects in the housing market.
 - ⇒ Test for pre-trends ahead of experienced MW changes through dynamic model.
 - ⇒ Check if there are housing supply responses around MW or experienced MW changes.

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.

Leads and lags of statutory MW

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.

Leads and lags of statutory MW

Byproduct advantage: Allows to assess dynamics of the effect.

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.

Leads and lags of statutory MW

Byproduct advantage: Allows to assess dynamics of the effect.

We also estimate an **Arellano-Bond panel specification** that adds the lagged dependent variable as control.

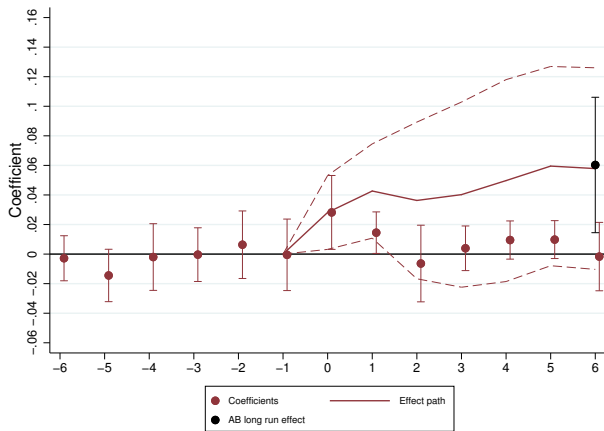
Results

Static Model

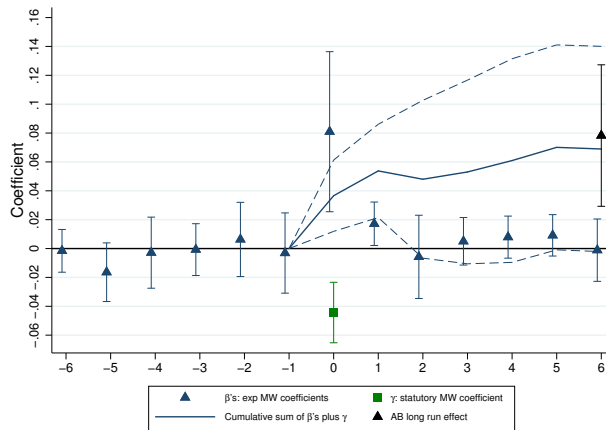
	$\Delta \underline{w}_{ict}^{\text{exp}}$	$\Delta \ln r_{ict}$		
	(1)	(2)	(3)	(4)
$\Delta \ln \underline{w}_{ict}$	0.8924*** (0.0319)	0.0258** (0.0124)		-0.0383* (0.0206)
$\Delta \underline{w}_{ict}^{\text{exp}}$			0.0317** (0.0131)	0.0718** (0.0293)
$\Delta \ln \underline{w}_{ict} + \Delta \underline{w}_{ict}^{\text{exp}}$				0.0335*** (0.0130)
Wage controls	Yes	Yes	Yes	Yes
Employment controls	Yes	Yes	Yes	Yes
Establishment-count controls	Yes	Yes	Yes	Yes
P-value equality				0.030
R-squared	0.946	0.022	0.022	0.022
Observations	107,814	107,814	107,814	107,814

Notes: All regressions include month FE. Economic controls correspond to the Financial, IT, and Professional and Business Services sectors in QCEW. Standard errors clustered at state level.

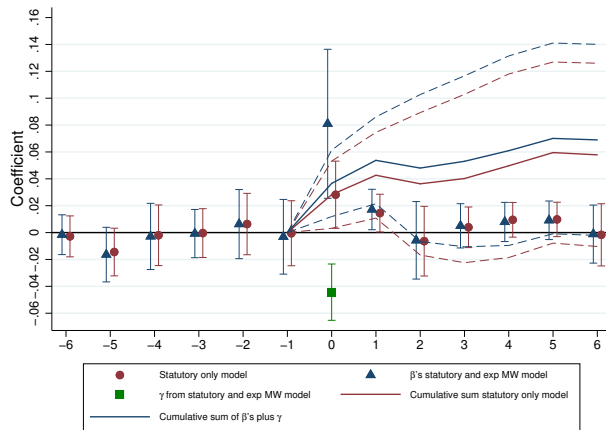
Dynamic Model: Statutory log MW Only



Dynamic Model: Experienced and Statutory MW



Dynamic Model: Comparison



Assessing the magnitude of the effects: Rationale

How much more income is generated by MW changes?

Assessing the magnitude of the effects: Rationale

How much more income is generated by MW changes?

One idea: use elasticity of average wages to MW $\Rightarrow \epsilon$.

Assessing the magnitude of the effects: Rationale

How much more income is generated by MW changes?

One idea: use elasticity of average wages to MW $\Rightarrow \epsilon$.

We use two different estimates of ϵ :

- We estimate it in our sample using QCEW data.
- We use an estimate from Cengiz et al. (2019).

Assessing the magnitude of the effects: Rationale

How much more income is generated by MW changes?

One idea: use elasticity of average wages to MW $\Rightarrow \epsilon$.

We use two different estimates of ϵ :

- We estimate it in our sample using QCEW data.
- We use an estimate from Cengiz et al. (2019).

Compute the pass-through dividing different rent elasticities by ϵ .

Assessing the magnitude of the effects: Results

	(1) QCEW regression	(2) Cengiz et al. (2019)
Panel A: Statutory MW Only		
Static rent elasticity ($\tilde{\beta}$)		0.026
Avg. Wage Elasticity (ϵ)	0.154	0.115
Pass-Through ($\tilde{\beta}/\epsilon$)	0.169	0.226
Panel B: Experienced MW controlling for statutory MW		
Static rent elasticity exp. MW (β)		0.072
Static rent elasticity stat. MW (γ)		-0.038
Avg. Wage Elasticity (ϵ)	0.154	0.115
Pass-Through workplace MW (β/ϵ)	0.466	0.624
Pass-Through workplace and residence MW ($\beta+\gamma/\epsilon$)	0.218	0.291

Robustness exercises

Data:

- Use fully unbalanced panel.
- Use fully balanced panel starting July 2015.
- Use re-weighted data to match socio-demographics of top-100 CBSA.

Robustness exercises

Data:

- Use fully unbalanced panel.
- Use fully balanced panel starting July 2015.
- Use re-weighted data to match socio-demographics of top-100 CBSA.

Identification:

- Pre-trends tests.
- Check effects of MW on housing supply.
- Allowing for feedback *a la* Arellano-Bond: sequential exogeneity.
- Change economic control sets.
- Allow for ZIP code-level heterogeneity in time paths.

Concluding Remarks

Conclusions

- Unlike employment effects, accounting for commuting patterns is key to study MW effects on the housing market.
 - ⇒ We propose a novel experienced MW measure accounting for the difference between workplace and residence.
 - ⇒ We find richer spatial patterns in the estimated effects.

Conclusions

- Unlike employment effects, accounting for commuting patterns is key to study MW effects on the housing market.
 - ⇒ We propose a novel experienced MW measure accounting for the difference between workplace and residence.
 - ⇒ We find richer spatial patterns in the estimated effects.
- A 10% increase in the experienced MW translates to a 0.7-1.1% increase in rents. If statutory MW also increases by 10%, the increase in rents would be 0.3-0.6%.

Conclusions

- Unlike employment effects, accounting for commuting patterns is key to study MW effects on the housing market.
 - ⇒ We propose a novel experienced MW measure accounting for the difference between workplace and residence.
 - ⇒ We find richer spatial patterns in the estimated effects.
- A 10% increase in the experienced MW translates to a 0.7-1.1% increase in rents. If statutory MW also increases by 10%, the increase in rents would be 0.3-0.6%.
- Ignoring the experienced MW would lead to a smaller effect only at residence.

Conclusions

- Unlike employment effects, accounting for commuting patterns is key to study MW effects on the housing market.
 - ⇒ We propose a novel experienced MW measure accounting for the difference between workplace and residence.
 - ⇒ We find richer spatial patterns in the estimated effects.
- A 10% increase in the experienced MW translates to a 0.7-1.1% increase in rents. If statutory MW also increases by 10%, the increase in rents would be 0.3-0.6%.
- Ignoring the experienced MW would lead to a smaller effect only at residence.
- Landlords pocket an average of at least 22 percent of the extra income generated by the MW increase.

Next Steps

- Explore heterogeneity of estimated elasticities by ZIP code characteristics.
- Micro-found our model to compute welfare changes of MW workers, firms, and landlords.
- Use estimated model to compute rent changes under counterfactual MW policies:
 - Effect of raising federal MW to \$15.
 - Effect of local MWs within metropolitan areas.

Appendix

Descriptive Statistics of Zillow Sample Compared to U.S.

	U.S.	Top 100 CBSA	Full Panel	Est. Panel
Population (millions) (2010)	311.18	189.71	110.17	50.62
Population as share of U.S.	1	0.61	0.35	0.16
Housing Units (millions) (2010)	132.83	78.74	46.72	21.32
Housing Units as share of U.S.	1	0.59	0.35	0.16
Urban Share (2010)	0.46	0.75	0.96	0.97
College Share (2010)	0.31	0.39	0.44	0.44
African-American Share (2010)	0.09	0.12	0.15	0.17
Hispanic Share (2010)	0.10	0.14	0.17	0.19
Elder Share (2010)	0.15	0.13	0.12	0.11
Poor Share (2010)	0.15	0.14	0.14	0.13
Unemployed Share (2010)	0.09	0.09	0.09	0.09
Mean HH income (2010)	52,492.56	62,773.64	65,475.16	66,919.72
Rent House Share (2010)	0.29	0.35	0.38	0.38
Unique zipcodes	38,893	14,583	3,315	1,305
Mean SFCC psqft rent			1.30	1.27

Notes: The table shows characteristics of four sets of U.S. postal service ZIP codes. All demographic information comes from the 2010 Census and the 5-years 2008-2012 ACS.

Proof of Proposition 1

Fully differentiate the equilibrium condition wrt $\ln(r_i)$ and $\{\ln(w_j)\}_{j \in Z}$ and rearrange to get:

$$\left(\sum_z \pi_{iz} \xi_{iz}^y \epsilon_{iz}^z d \ln \underline{w}_z \right) + \left(\sum_z \pi_{iz} \xi_{iz}^y \epsilon_{ij}^i \right) d \ln \underline{w}_i = \left(\eta_i - \sum_z \pi_{iz} \xi_{iz}^r \right) d \ln r_i$$

where

- $\pi_{iz} = \frac{L_{iz}}{L_i}$: *share* of i 's residents working in z ;
- $\xi_{iz}^r = \frac{dH_{iz}}{dr} \frac{r_i}{\sum_z \pi_{iz} H_{iz}}$ and $\xi_{iz}^y = \frac{dH_{iz}}{dy} \frac{y_{iz}}{\sum_z \pi_{iz} H_{iz}}$: elasticities of *housing demand* wrt r and y ;
- $\epsilon_{ij}^i = \frac{dy_{iz}}{d\underline{w}_i} \frac{\underline{w}_i}{y_{iz}}$ and $\epsilon_{iz}^z = \frac{dy_{ij}}{d\underline{w}_z} \frac{\underline{w}_z}{y_{iz}}$: elasticities of *disposable income* wrt \underline{w}_i and \underline{w}_z ; and
- $\eta_i = \frac{dD_i}{dr_i} \frac{r_i}{D_i}$: elasticity of *housing supply*.

Proof of Proposition 1

Signs of the coefficients are as follows:

$$\sum_z \pi_{iz} \underbrace{\xi_{iz}^y \epsilon_{iz}^z}_{(+)} d \ln \underline{w}_z + \sum_z \pi_{iz} \underbrace{\xi_{iz}^y \epsilon_{iz}^i}_{(-)} d \ln \underline{w}_i = \underbrace{\left(\eta_n - \sum_z \pi_{iz} \xi_{iz}^r \right)}_{(+)} d \ln r_i$$

which proves the first part of the proposition.

Proof of Proposition 1

Signs of the coefficients are as follows:

$$\sum_z \pi_{iz} \underbrace{\xi_{iz}^y \epsilon_{iz}^z}_{(+)} d \ln \underline{w}_z + \sum_z \pi_{iz} \underbrace{\xi_{iz}^y \epsilon_{iz}^i}_{(-)} d \ln \underline{w}_i = \underbrace{\left(\eta_n - \sum_z \pi_{iz} \xi_{iz}^r \right)}_{(+)} d \ln r_i$$

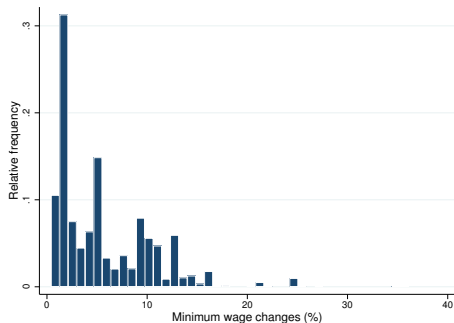
which proves the first part of the proposition.

Assume now that $\xi_{iz}^y = \xi_i^y$, $\epsilon_{iz}^i = \epsilon_i^i$ and $\epsilon_{iz}^z = \epsilon_i^z \forall i \in \mathbb{Z}$. Then,

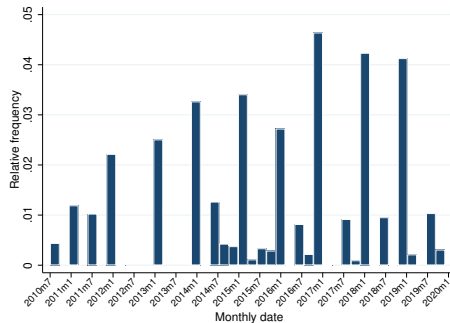
$$d \ln r_i = \underbrace{\frac{\xi_i^y \epsilon_i^L}{\eta_i - \sum_j \pi_{ij} \xi_{ij}^r}}_{\beta_i > 0} \underbrace{\sum_j \pi_{ij} d \ln \underline{w}_j}_{\text{Exp. log MW at residence}} + \underbrace{\frac{\xi_i^y \epsilon_i^R}{\eta_i - \sum_j \pi_{ij} \xi_{ij}^r}}_{\gamma_i < 0} \underbrace{d \ln \underline{w}_i}_{\text{Statut. log MW at residence}}.$$

Distribution of (positive) MW changes

(a) Intensity



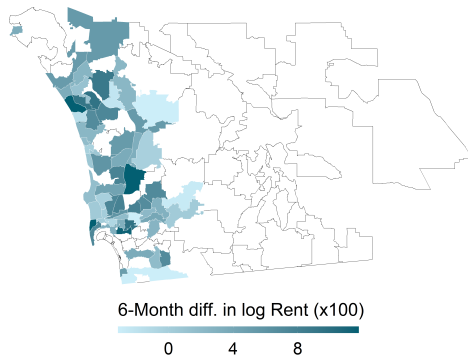
(b) Timing



Notes: The histograms show the distribution of positive MW changes in the full sample of ZIP codes available in the Zillow data.

Change in rents after CA MW Increase of January 2019 in San Diego

[Go Back](#)



Notes: The figure shows the change in log median rents in Zillow between December 2018 and June 2019.

Dynamic model: Statutory MW

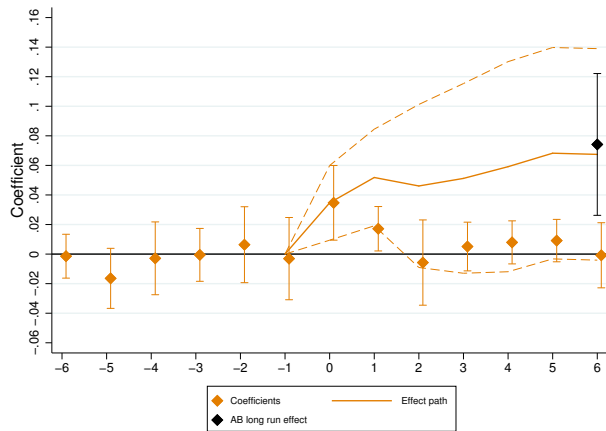
Adding leads and lags of the statutory MW:

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

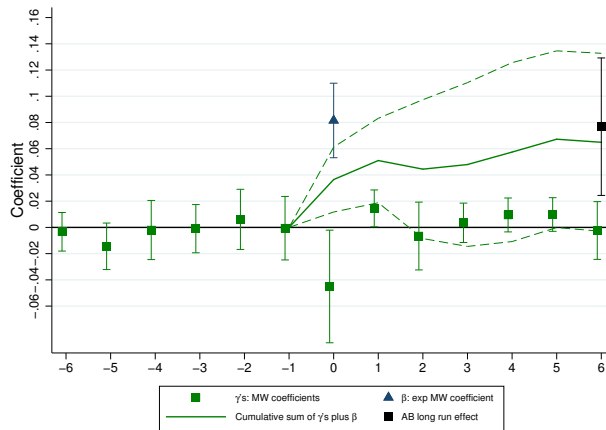
where $\{\gamma_r\}_{r=-s}^s$ are dynamic effects of the statutory log MW.

[Go Back](#)

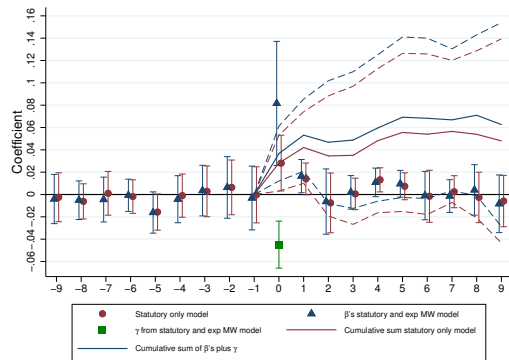
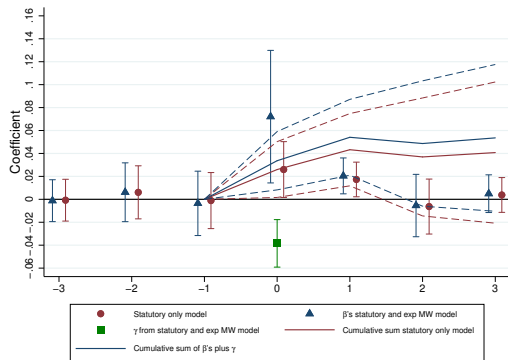
Dynamic Model: Experienced log MW Only



Dynamic Model: Experienced and Statutory MW (alternative)



Window size perturbations



Go Back