A Dynamic Model of Residential Sorting Using Aggregate Data: Welfare Implications of Urban Fracking

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Introduction

The Urban Fracking Boom

- Shale Revolution
  - Advances in horizontal drilling and hydraulic fracturing (fracking) have unlocked previously unviable shale formations.
  - Profitable extraction of natural gas has been made possible even in densely populated urban areas
- Some U.S. cities that lie on top of shale play now displays a new 'urban' feature - fracking activities.
- Tarrant County, TX
  - Urban county (2.1 Million population), houses the city of Fort Worth
  - 4828 Shale gas wells
  - 1 Million population resides within 1 mile radius from oil/gas activity

Background - Spacial Spread of Urban Fracking

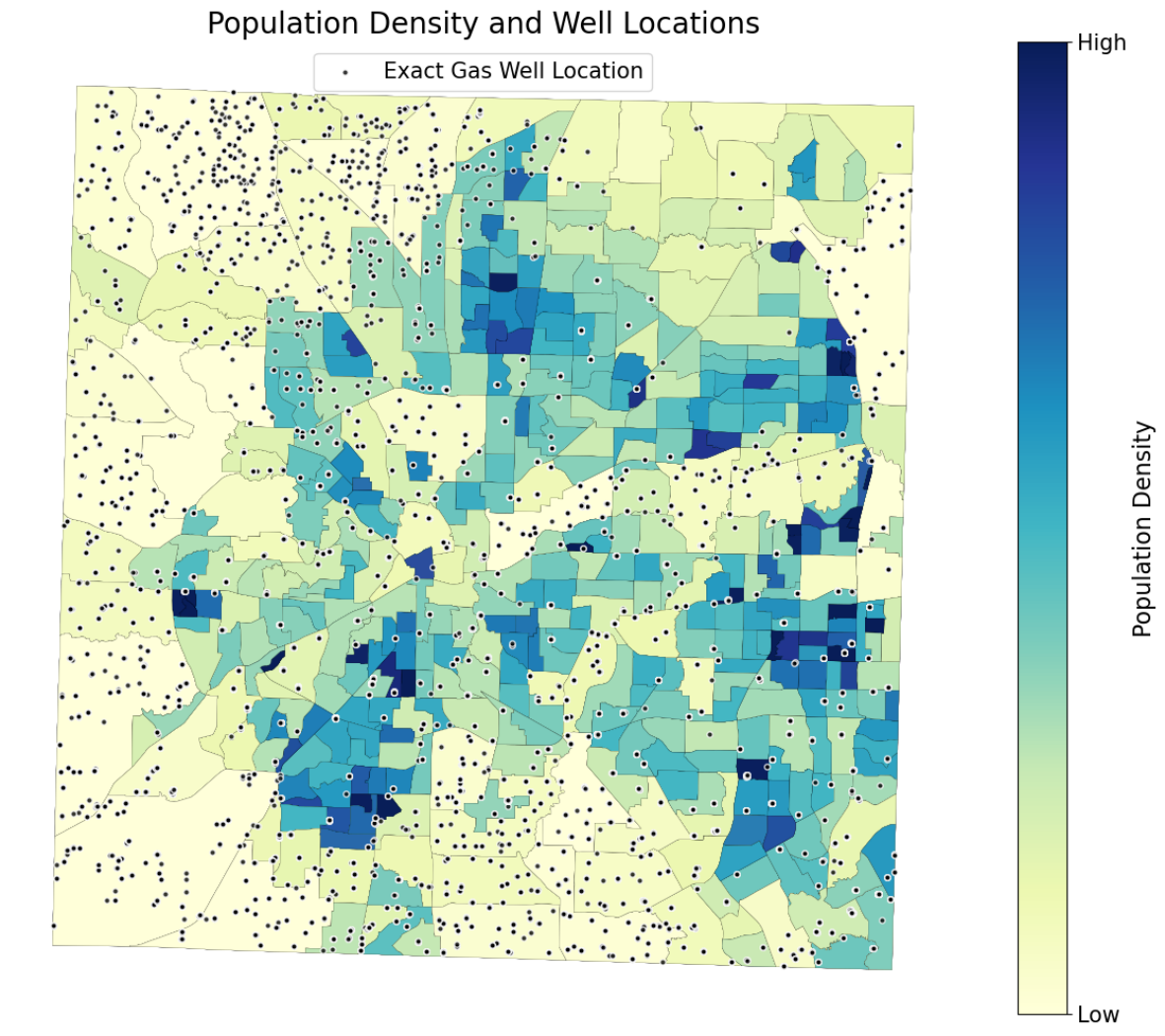


Figure 1: Location of Gas Wells, and Population Density in Tarrant County

Background - Policy Debate





Tarrant County Reisdnets Calling for Fracking Ban[1].

[1]Source: Google Search

Background - Fracking in Backyards



Figure 2: A Google Street View of 'Backyard Fracking'

→The Street View

Research Question

- Overall Welfare implication of urban fracking is unclear
  - **Q1: How does urban fracking affect the resident's welfare?**
    - Direct - Newly Added Disamenity
    - Indirect - Housing Cost Adjustment, Racial Re-sorting of Neighborhoods
- Distributional impact is also unclear - Possible "reverse-gentrification"
  - **Q2: How heterogeneous are responses across racial/ethnic groups?**
  - **Q3: What is the distributional impact of urban fracking?**

This Paper...

1. Construct a Single Agent Dynamic Discrete (SDDC) model of location choice to estimate migration patterns and welfare effects
   - Dynamic Discrete Choice Models: Rust (1987), Arcidiacono and Miller (2011), Aguirregabiria et al. (2021), Bayer et al. (2016), Almagro and Domínguez-Iino (2024).
   - **I propose a novel method to estimate SDDC models using only high-dimensional aggregate data.**
   - **I propose an alternative approach to construct fully dynamic counterfactuals, avoiding the curse of dimensionality.**
2. Calculate heterogeneous willingness to pay to avoid fracking
   - Urban Housing Market Dynamics and Sorting: Tiebout (1956), Bayer et al. (2007), Heblich et al. (2020), Borsky et al. (2024), Almagro et al. (2023).
   - **First to estimate the impact of urban fracking on migration patterns and its racial heterogeneity.**
3. Simulate neighborhood changes and distributional consequences through a gentrification counterfactual
   - Environmental Justice Literature and Sorting: Tiebout (1956), Bayer et al. (2007), Heblich et al. (2020), Borsky et al. (2024), Almagro et al. (2023), Banzhaf et al. (2019), Cain et al. (2024), Timmins and Vissing (2022), Rous et al. (2020), Depro et al. (2015).
   - **First to demonstrate distributional consequences of urban fracking in welfare, especially through counterfactuals in a general equilibrium.**

Data

Main Data:

- **Where the wells are**
  - Texas Railroad Commission Data: Exact location and permit dates for all shale gas wells.
  - 4,828 shale gas wells in Tarrant County.
- **Where the people are**
  - Aggregate Census Data: Decennial Census and American Community Survey (ACS).
  - Aggregate housing and demographic characteristics by census tract.
  - 437 census tracts in Tarrant County.
  - Time periods: 2000, 2007, 2014, 2021.

Motivating Facts

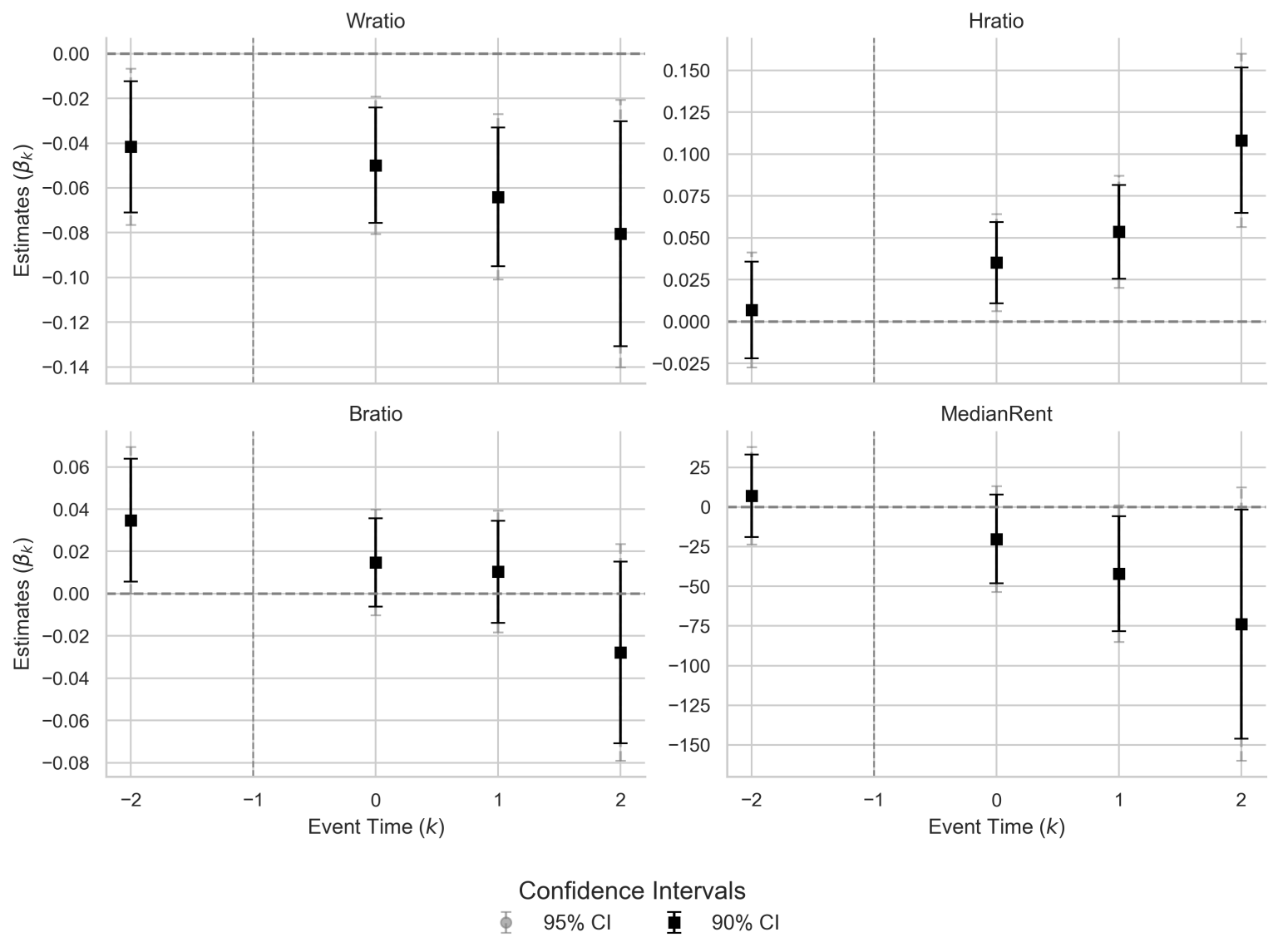


Figure 3: Change in Key Variables After the Initial Development

*Equation: $Y_{jr} = \alpha + \sum_{k \in \{-2,0,1,2\}} \beta_k DEV_{jk} + X_{jt}\beta_X + \varphi_c + \varphi_t + \epsilon_{jt}$

Dynamic General Housing Equilibrium Model

Model - Dynamic Residential Location Choice

Consider a forward-looking group g resident i who maximizes their expected utility:

$$\lim_{T\to\infty} E[\sum_{r=t}^{T} \beta^{r-t} u_{ijgt}(\cdot)|\Omega_t]$$

- Currently living at d_{it} at t, she chooses among $j = 1, ..., J$ census tracts and an outside option $(J + 1)$.
- State variables Ω_t summarize location characteristics $(p_{jt}, X_{jt}, \xi_{jt})$.
- Race/ethnicity group $g \in \{W, H, B\}$ affects utility parameters and moving costs sc_{gt}.
- Flow utility:

$$u_{ijgt} = f(p_{jt}, X_{jt}, \xi_{jt}; \theta_g) - sc_{gt} \cdot \mathbf{1}(d_{it} \neq j) + \epsilon_{ijt}$$

- Outside option $J + 1$ is a terminal option and

$$u_{iJ+1gt} = 0 - sc_{gt} \cdot \mathbf{1}(d_{it} \neq J + 1) + \epsilon_{iJ+1t}$$

- Choice-specific value function[2] ▸ Bellman Equation :

$$CV_{jt} = \underbrace{f_{jt}(\Omega_t)}_{\text{per-period mean utility}} + \beta \underbrace{E[EV(j, \Omega_{t+1}) \mid \Omega_t]}_{\text{continuation value}}$$

- $\epsilon_{ijt} \sim$ T1 Extreme Value, moving probability from k to j (Hotz and Miller, 1993):

$$P_{jkt} = \frac{\exp(CV_{jt} - sc_t \cdot \mathbf{1}(j \neq k))}{\sum_{l=1}^{J+1} \exp(CV_{lt} - sc_t \cdot \mathbf{1}(l \neq k))}$$

- Housing demand:

$$\underbrace{\overset{\text{(Data)}}{N_{jt}}}_{\text{(Total Population at } j\text{)}} = \sum_{g \in G} \sum_{k \in J} \underbrace{\overset{\text{(Data)}}{N_{kgt-1}}}_{\text{(Population. } g \text{ at } k\text{)}} \times \underbrace{\overset{\text{(Model)}}{P_{jkgt-1}}}_{\text{(Prob. move from } k \text{ to } j\text{)}}$$

- Housing market clears through a supply function (Almagro et al., 2023):

$$S_{jt}(p_{jt}) = \lambda_{jt} p_{jt}^{\psi}$$

▸ Supply Details

[2] Continuation Value: Discounted future utilites from optimal path of moves.

Model: State Transition of Choice-Specific Values

Following Bayer et al., 2016, I introduce the following assumption on how residents form expectations about future values.

Residents' Expectation Formation:

- I allow residents to **directly** predict future CV_{t+1} based on current observable states, and CV_t.

Value Transition Equation:

$$CV_{jt} = \gamma_{0,j} + \sum_{l=1}^{L} \gamma_{1,l} CV_{j,t-l} + \sum_{l=1}^{L} X'_{j,t-l}\gamma_{2,l} + \omega_{j,t}, \;\; \omega \sim i.i.d.\; N(0, \sigma)$$

Key Features:

- Transition depends on **observable characteristics** and **past CV**.
- Conditioned on state space, the transition of value is defined on choice set.
- Future CV prediction is empirical, no parametric assumption on individual evolution of state variables.

Dynamic Demand Estimation

Demand Estimation Procedure Overview ▸ Flow-Chart

Stage 1: Recover Values and Switching Costs ▸ Detail

- Inner loop: Given sc_g, update CV_{gt} via BLP-style contraction to match observed future shares and the shares predicted by the model:

$$CV_{gt}^{m+1} = CV_{gt}^{m} + \overline{\ln S_{gt+1}} - \widetilde{\ln S_{gt+1}}$$

- Outer loop: Adjust sc to match predicted and observed non-moving probabilities.

Stage 2: Recover Per-Period Utilities ▸ Detail

- Simulate future CV_{gt+1} and approximate expected value function:

$$\mathbb{E}[EV(j, \Omega_{t+1})|\Omega_t] \approx \frac{1}{R}\sum_{r=1}^{R}\left(\gamma + \ln\left(\sum_{l}\exp(CV_{glt+1}^{(r)} - sc_{gt+1}\mathbf{1}(l \neq j))\right)\right)$$

- Invert Bellman equation to recover f_{jt}.

Stage 3: Estimate Preference Parameters ▸ Detail

- Regress recovered $\hat{f}_{jgt}$ on housing price, demographics, and amenities using IV-GMM.

Dynamic Housing Demand Estimates

	White	Hispanic	Black
Number of Wells	-0.0266***	-0.0195**	-0.0561***
	(0.0097)	(0.0091)	(0.0203)
Median Rent (1000$)	-0.0013*	-0.0032***	-0.0053***
	(0.0008)	(0.0007)	(0.0013)
Share Hispanic	-0.9959*	2.2571***	0.2771
	(0.5818)	(0.5722)	(1.2615)
Share Black	-2.7225***	0.4258**	4.5140***
	(0.2192)	(0.1732)	(0.4197)
Median Year Built	0.0274***	0.0265***	0.0683***
	(0.0052)	(0.0058)	(0.0119)
Median Number of Rooms	0.1103	0.2719***	0.4711***
	(0.0811)	(0.0781)	(0.1519)
Share Owner-Occupied	0.0006***	0.0008***	0.0010***
	(0.0001)	(0.0001)	(0.0002)
Violent Crime Rate	-0.0008***	-0.0001	-0.0012*
	(0.0003)	(0.0003)	(0.0006)
City Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
N	1170	1170	1170

$$\textbf{WTP}_{\textbf{(Avoid)}} = \frac{\beta_{\text{Wells}}}{\beta_{\text{Rent}}}$$

Group	WTP, Δ Wells
White	\$19.86/Month
	(13.38)
Hispanic	\$6.17/Month
	(3.17)
Black	\$10.59/Month
	(4.63)

Notes: Standard errors in parentheses. Wild bootstrapped standard errors clustered at census tract level.

Willingess to avoid is per-period willingness to avoid, following Bayer et al., 2016. Significance levels: $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$.

Counterfactual Analysis, and Welfare

Counterfactual Construction in Dynamic Model

Challenge: Counterfactual construction in a dynamic model is non-trivial because values satisfy a recursive Bellman system (Rust, 1987): ▸ Mechanism

$$CV_{jt} = f_{jt} + \beta \, \mathbb{E}\left[\ln\left(\exp(CV_{jt+1}) + \sum_{l \neq j} \exp(CV_{lt+1} - sc_{t+1}) \right) \middle| \Omega_t \right] + \gamma$$

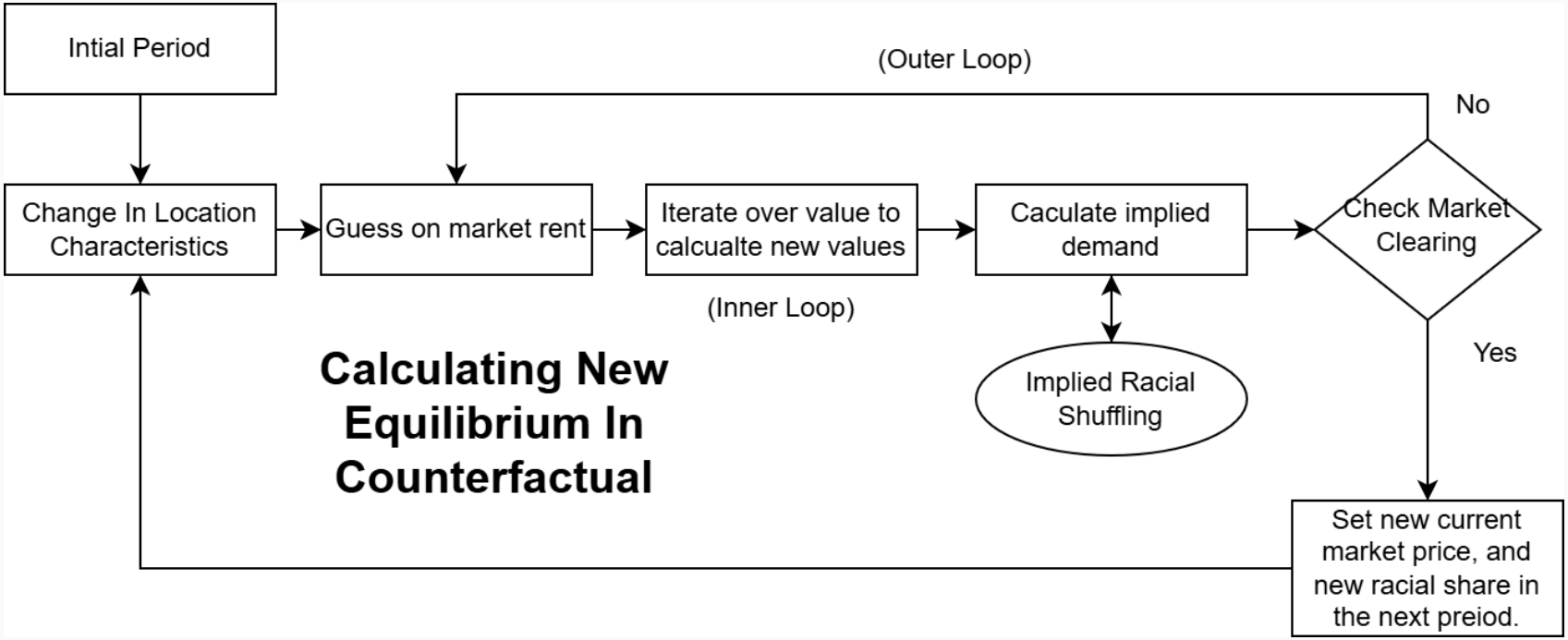
Thus: Even a local change in f_{jt} triggers a system-wide adjustment in CV_t, requiring to find a new fixed point across all choices (limited by dimensionality).

Solution: Re-define value iteration **on choice set**, not entire state space.
$\Rightarrow$ Results in a unique solution. (Banach Fixed Point Theorem) ▸ Details

Advantages:

- Dimensionality grows linearly with number of choices (avoiding curse of dimensionality).
- Faster convergence than conventional value iteration.
- Iteration is contractive $\Rightarrow$ Unique solution for any initial guess. ▸ Theorem

Counterfactual – Equilibrium

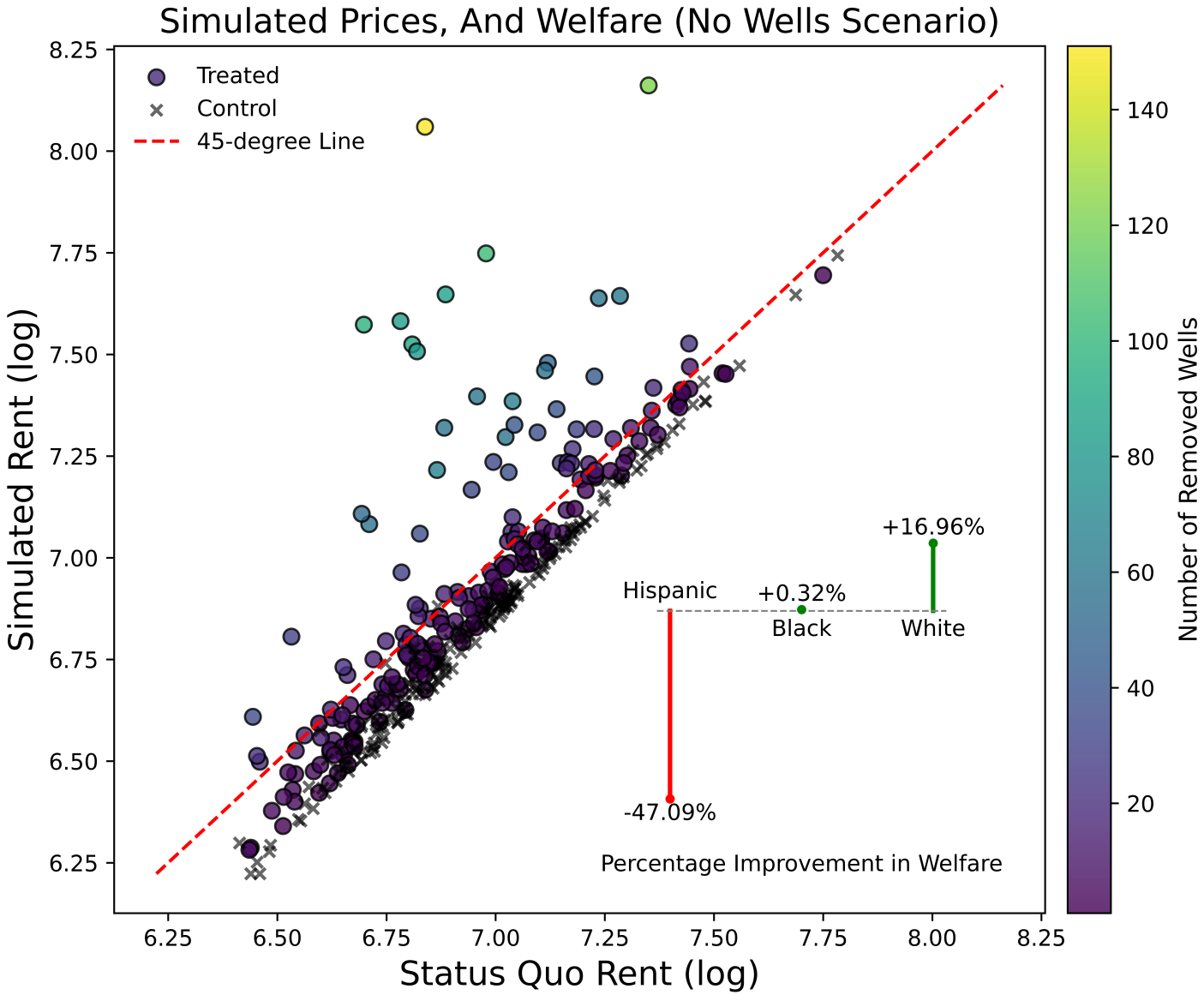


Key Assumption: Residents hold their baseline belief parameters about the evolution of states under counterfactual scenarios. ▸ Discussion

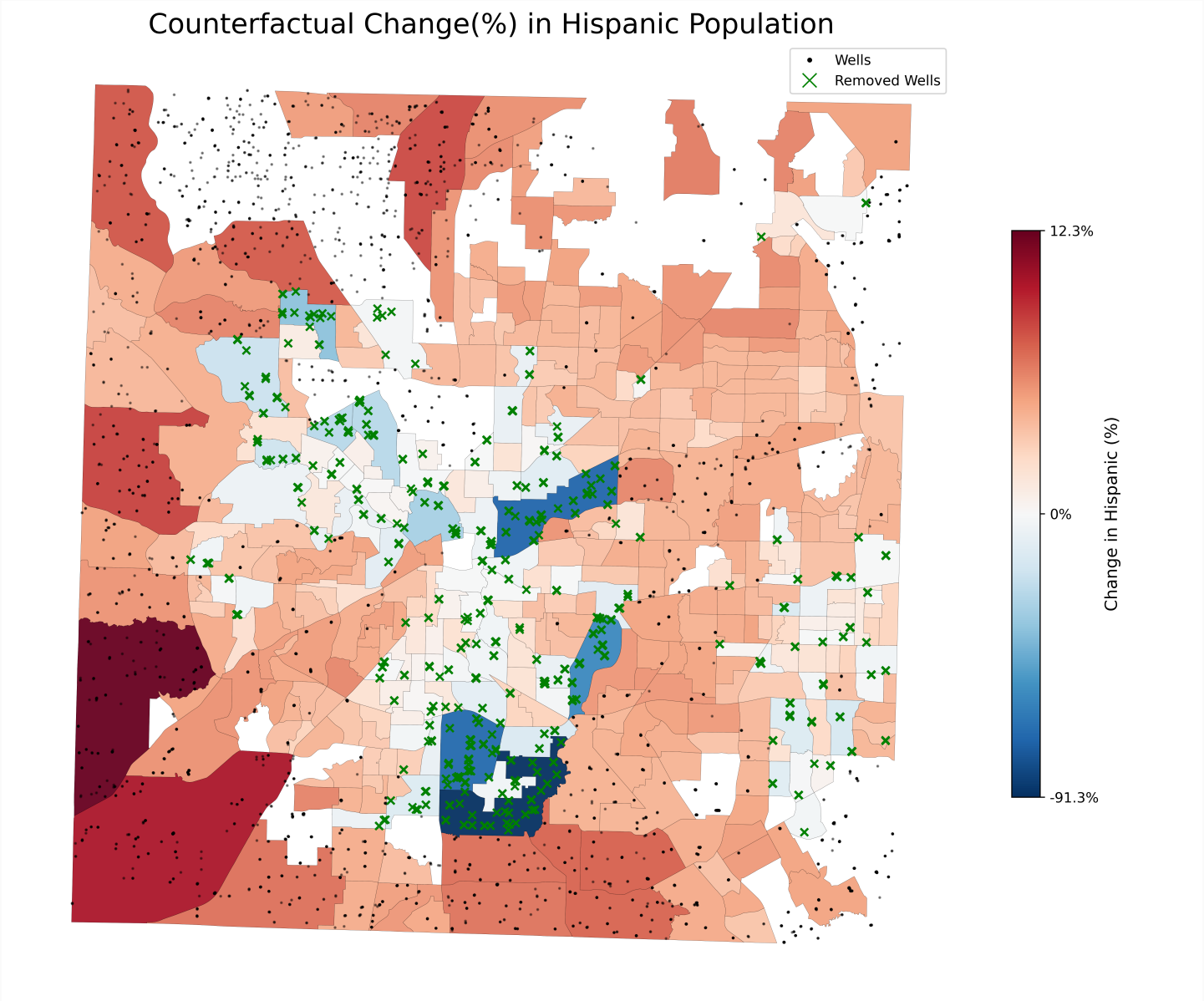
- **Counterfactual 1:** Remove all wells in Tarrant County
  - Analyze changes in equilibrium price and welfare
- **Counterfactual 2:** Ban fracking in predominantly Hispanic tracts
  - Examine re-sorting dynamics and gentrification patterns

Counterfactual - Removing All the Wells

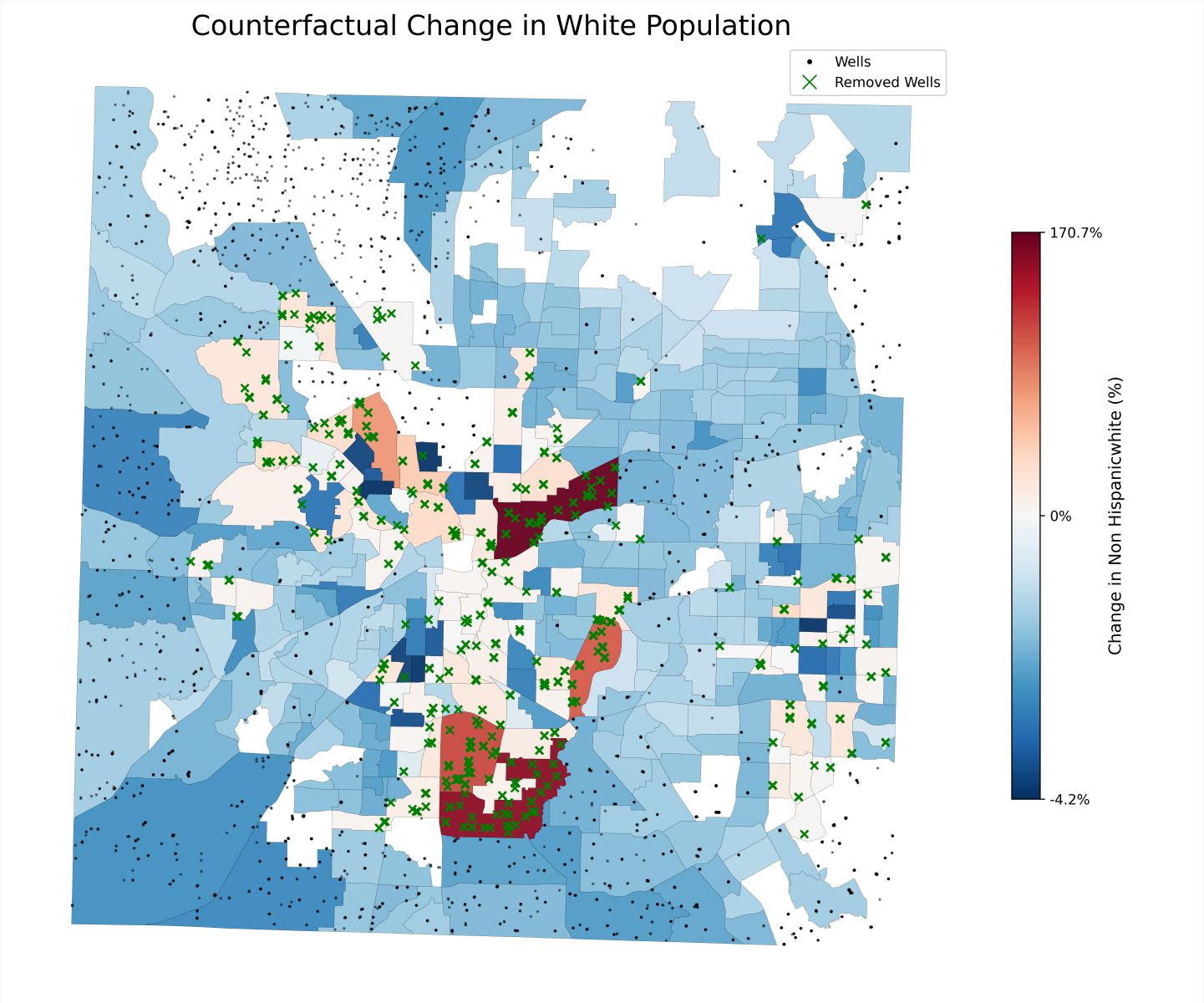
No Sorting



Counterfactual - Targeted Ban (Hispanic Tracts)



Counterfactual - Targeted Ban (Hispanic Tracts)



Conclusion

- I showed that
  - There is significant racial heterogeneity in trading off fracking v.s. living cost
  - White are worse off, hispanic population are better off after fracking.
  - Banning fracking in Hispanic neighborhoods cause gentrification
- I constructed a dynamic model of residential sorting *only* using aggregate census data
  - Proposed new methods for estimation and counterfactuals
- Ongoing works
  - More policy-relevant counterfactuals
    - Housing subsidy to prevent sorting toward gas wells
    - Equitable value transfer from fracking firms to residents

Thank You!

Estimation Stage 1: Recover CV_t and Switching Cost sc

Objective: Recover choice-specific value functions (CV_t) and switching costs (sc) from observed **future aggregate shares**.

Inner-loop: Update CV_t iteratively to match observed and predicted future shares

- Given a guess of switching cost sc_t,
- Iterate over CV_t using BLP-style contraction mapping:

$$CV_{gt}^{m+1} = CV_{gt}^{m} + \ln \overline{S_{gt+1}} - \ln \widetilde{S_{gt+1}}$$

where

- $\ln \overline{S_{gt+1}}$: Observed log future share
- $\ln \widetilde{S_{gt+1}}$: Predicted log future share from current CV^m

Outer-loop: Update sc_t to match predicted and observed non-moving probabilities

- Adjust sc so that the predicted staying probability matches ACS data.

▸ Back to Overview

Estimation Stage 2: Recover Per-Period Utilities f_{jt}

Goal: Following Bayer et al., 2016, recover f_{jt} from estimated choice-specific values $\widehat{CV}_{jt}$.

Choice-specific values:

$$CV_{jt} = f_{jt} + \beta\, \mathbb{E}[EV(j, \Omega_{t+1})]$$

Step 1: Approximate $\mathbb{E}[EV(j, \Omega_{t+1})]$ (Monte Carlo)

- Simulate future CV_{t+1} from observed transitions of CV_t.
- Use log-sum formula (Rust, 1987):

$$\mathbb{E}[EV(j, \Omega_{t+1})] \approx \frac{1}{R} \sum_{r=1}^{R} \left(\gamma + \ln \left(\sum_{l} \exp \left(CV_{lt+1}^{(r)} - sc_{t+1} \cdot \mathbf{1}(l \neq j) \right) \right) \right)$$

Step 2: Invert Bellman Equation

$$\widehat{f}_{jt} = CV_{jt} - \beta\, \widehat{\mathbb{E}}[EV(j, \Omega_{t+1})]$$

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Estimation Stage 3: Estimate Preference Parameters

Goal: Recover preference parameters θ_g from estimated per-period mean utilities.

- Linear specification:

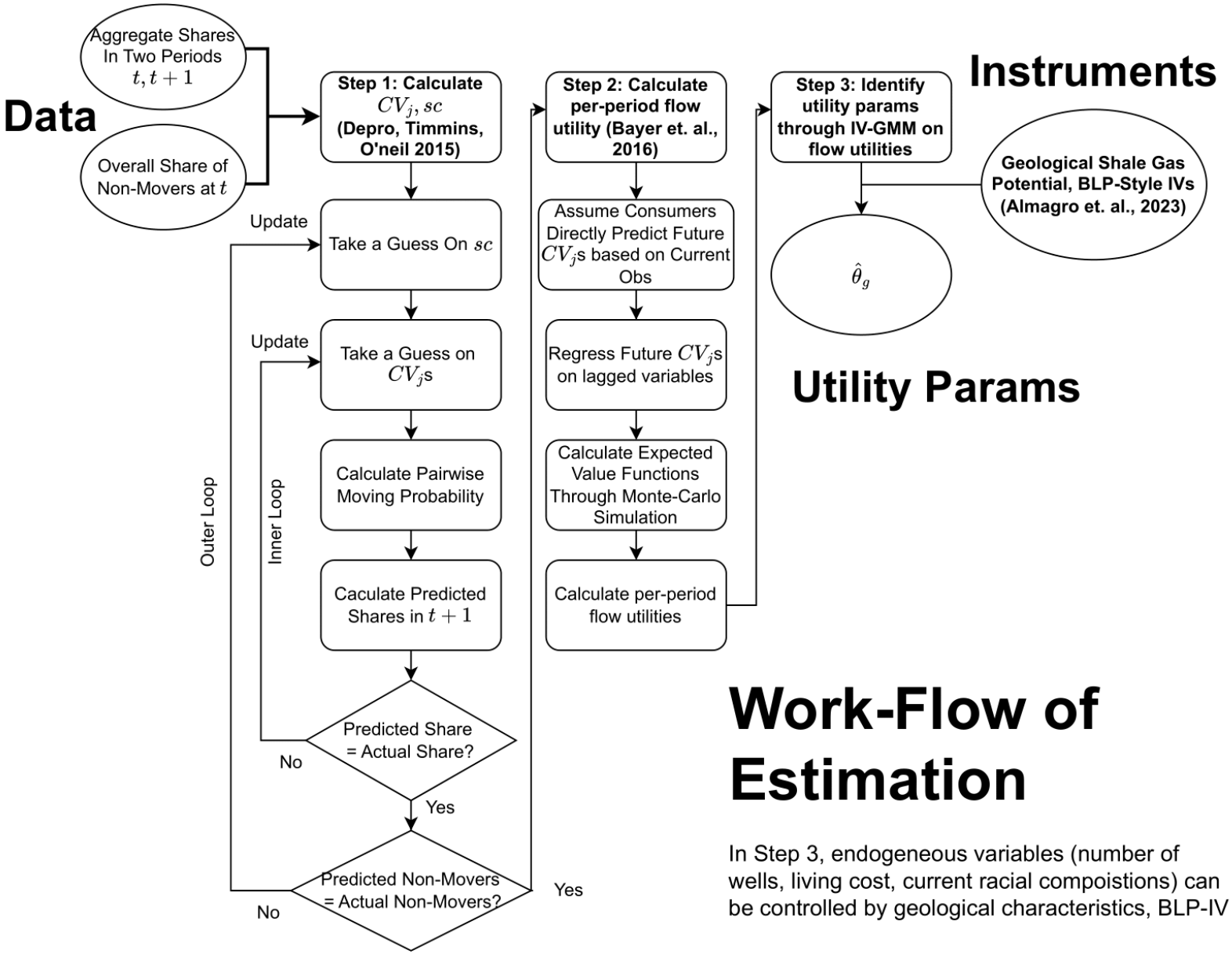
$$\hat{f}_{jgt} = \theta_{g0} + \theta_{gp} p_{jt} + X'_{jt}\theta_{gx} + \theta_{g,j} + \theta_{g,t} + \xi_{gjt}$$

- I use bootstrapped IV-GMM, accounting for endogenous ξ_{gjt}
  - Endogeneous: p_{jt}, racial homophily, number of wells
  - p_{jt}, racial homophily $\Leftarrow$ Exogenous characteristics of distant neighborhood (Almagro et al., 2023)
  - number of wells $\Leftarrow$ Shale depth, Average days of well construction

▸ Back to Overview

Estimation Flow Chart

▸ Back to Overview



Work-Flow of Estimation

In Step 3, endogeneous variables (number of wells, living cost, current racial compoistions) can be controlled by geological characteristics, BLP-IV

Formal Discussion of the Proposed Value Iteration

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Theorem

For any counterfactual $\overline{f}_t$, define operator T as $T : R^{J+1} \to R^{J+1}$ such that

$$T(CV_{j,t}) = \overline{f}_{j,t} + \beta E\left[ln\left(exp(CV_{j,t+1}) + \sum_{l \in J \setminus \{j\}} exp(CV_{l,t+1} - sc_{t+1}) \right) + \gamma \mid \Omega_t \right]$$

where the dynamic relationship between CV_t and CV_{t+1} is given by

$$CV_{j,t+1} = \gamma_0 + \gamma_1 CV_{j,t} + X_{j,t}\gamma_2 + \omega_{j,t}$$

Then, T is contractive if $\beta\gamma_1 < 1$.

Proof.

The proof is similar to Rust, 1987. □

Corollary

With any bounds on CV_t, there exist a unique fixed point $\overline{CV}_t$ such that

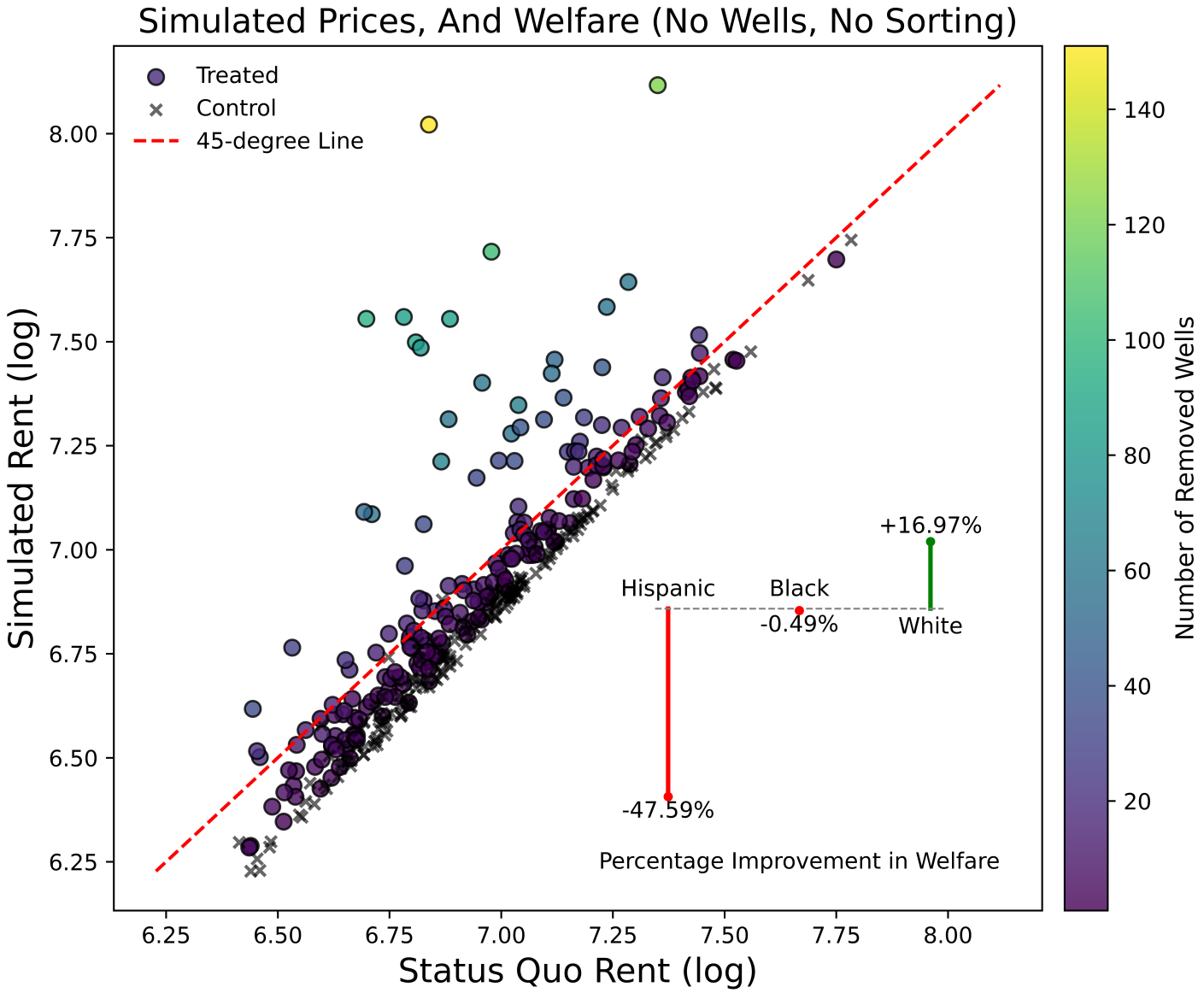
$$\overline{CV}_{jt} = \overline{f}_j(\Omega_t) + \beta E\left[ln\left(exp(\overline{CV}_{jt+1}) + \sum_{l \in J \setminus \{j\}} exp(\overline{CV}_{lt+1} - sc_{t+1}) \right) + \gamma \mid \Omega_t \right], \quad \forall j.$$

Proof.

Follows the Banach's fixed point theorem. □

Counterfactual - Removing All the Wells (No sorting)

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Bellman Equation

Bellman equation:

$$V(\Omega_t, d_{it}, \epsilon) = \max_{d_{it}; j \in J \setminus \{d_{it}\}} \begin{Bmatrix} f_{d_{it}}(\Omega_t) + \epsilon_{id_{it}t} + \beta E[EV(d_{it}, \Omega_{t+1})|\Omega_t], \\ f_j(\Omega_t) + \epsilon_{ijt} - sc_t + \beta E[EV(j, \Omega_{t+1})|\Omega_t] \end{Bmatrix}.$$

Note that switching cost introduces state dependency through lock-in effect. ▸ Back

Model: Housing Supply

I allow housing stock to respond to housing cost by the following rule.

Housing Supply:

$$S_{jt}(p_{jt}) = \lambda_{jt} p_{jt}^{\psi}$$

Key Features:

- ψ: Housing supply elasticity, taken from Baum-Snow and Han, 2024.
- λ_{jt}: Tract-time-specific supply shifter, calibrated to match observed prices and quantities. Almagro et al., 2023
- Finite elasticity of supply adjusts equilibrium price facing any change in total demand.

▸ Back

Counterfactual

Back

Constructing counterfactual is non-trivial in dynamic model:

Recursive system of values (Following Bellman Principle):

$$CV_{jt} = f_{jt} + \beta \, \mathbb{E}\left[\ln\left(\exp(CV_{jt+1}) + \sum_{l \neq j} \exp(CV_{lt+1} - sc_{t+1}) \right) |\Omega_t \right] + \gamma$$

Key Mechanism:

- $f_{jt} \uparrow \Rightarrow CV_{jt} \uparrow$
- $CV_{jt} \uparrow \Rightarrow CV_{jt+1} \uparrow$ (via state transition) $\uparrow \Rightarrow CV_{jt} \uparrow\downarrow$
- $CV_{jt+1} \uparrow \Rightarrow$ Future $\mathbb{E}[EV(l, \Omega_{t+1})] \uparrow\downarrow$ for **all** $l \Rightarrow CV_{lt} \uparrow\downarrow$ for **all** l

Thus:

- Even a local change in f_{jt} triggers a **system-wide recursive adjustment**.
- Solving counterfactuals requires finding a new fixed point (on CV_t) across all choices and periods through value iteration.(Limited by curse of dimensionality?)

Counterfactual

Back

Note: The value iteration is defined on **Choice set**, not state space (which is Rust, 1987).

Value Iteration Overview:

- Given a counterfactual change from X_{jt} to $\overline{X}_{jt}$, and an inital guess $\overline{CV}^{o}_{jt}$,
- Iterate and find a new vector $(J+1 \times 1)$ of $\overline{CV}_t$ satisfying:

$$\overline{CV}_{jt} = \overline{f}_{jt} + \beta\, \mathbb{E}\left[\ln\left(\exp(\overline{CV}_{jt+1}) + \sum_{l \neq j} \exp(\overline{CV}_{lt+1} - sc_{t+1}) \right) \middle| \Omega_t \right] + \gamma$$

Where the future values are simulated according to

$$CV_{jt+1} = \gamma_{0,j} + \sum_{l=0}^{L-1} \gamma_{1,l} CV_{j,t-l} + \sum_{l=0}^{L-1} \overline{X'}_{j,t-l} \gamma_{2,l} + \omega_{j,t}$$

Proof: I prove that the iterative procedure to find updated $\overline{CV}_{jt}$ is contractive, leading to a unique solution for any initial guess $\overline{CV}^{0}_{jt}$ Theorem

Discussion: Using Baseline Belief in Counterfactual

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- Facing policy shocks, agents **Don't** update belief parameters formed from observed equilibrium paths.
  - Reflects a form of subjective or sticky expectations. (An et al., 2021; Carroll et al., 2020)
- **Limitation:** May mischaracterize long-run responses if agents are fully rational. (Lucas, 1976)
- Makes more sense when
  1. Residents have formed empirical belief from long-run observation of a stable equilibrium path
  2. State space is large
  3. Counterfactual change is small
- **High-dimensional dynamic counterfactual analysis in the literature:**
  - Impose perfect foresight/myopia in counterfactual when state space is large (Almagro and Domínguez-Iino, 2024)
  - Hold neighborhood characteristics fixed (Davis et al., 2021)
- Benefit: Provides an alternative than imposing perfect foresight/myopia.

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