

Lecture 7: Hedonics, Voting with Your Feet, and Why it's Not That Simple

Prof. Parthum
Environmental Economics
Econ 475

The “Characteristics” Model

Lancaster (1966) –

A New Approach to Consumer Theory

1. The good, per se, does not give utility to the consumer; it **possesses characteristics**, and these characteristics give rise to utility.

The “Characteristics” Model

Lancaster (1966) –

A New Approach to Consumer Theory

1. The good, per se, does not give utility to the consumer; it **possesses characteristics**, and these characteristics give rise to utility.
2. In general, a good will possess more than one characteristic, and **many characteristics will be shared by more than one good**.

The “Characteristics” Model

Lancaster (1966) –

A New Approach to Consumer Theory

1. The good, per se, does not give utility to the consumer; it **possesses characteristics**, and these characteristics give rise to utility.
2. In general, a good will possess more than one characteristic, and **many characteristics will be shared by more than one good**.
3. Goods in combination may possess characteristics different from those pertaining to the goods separately.

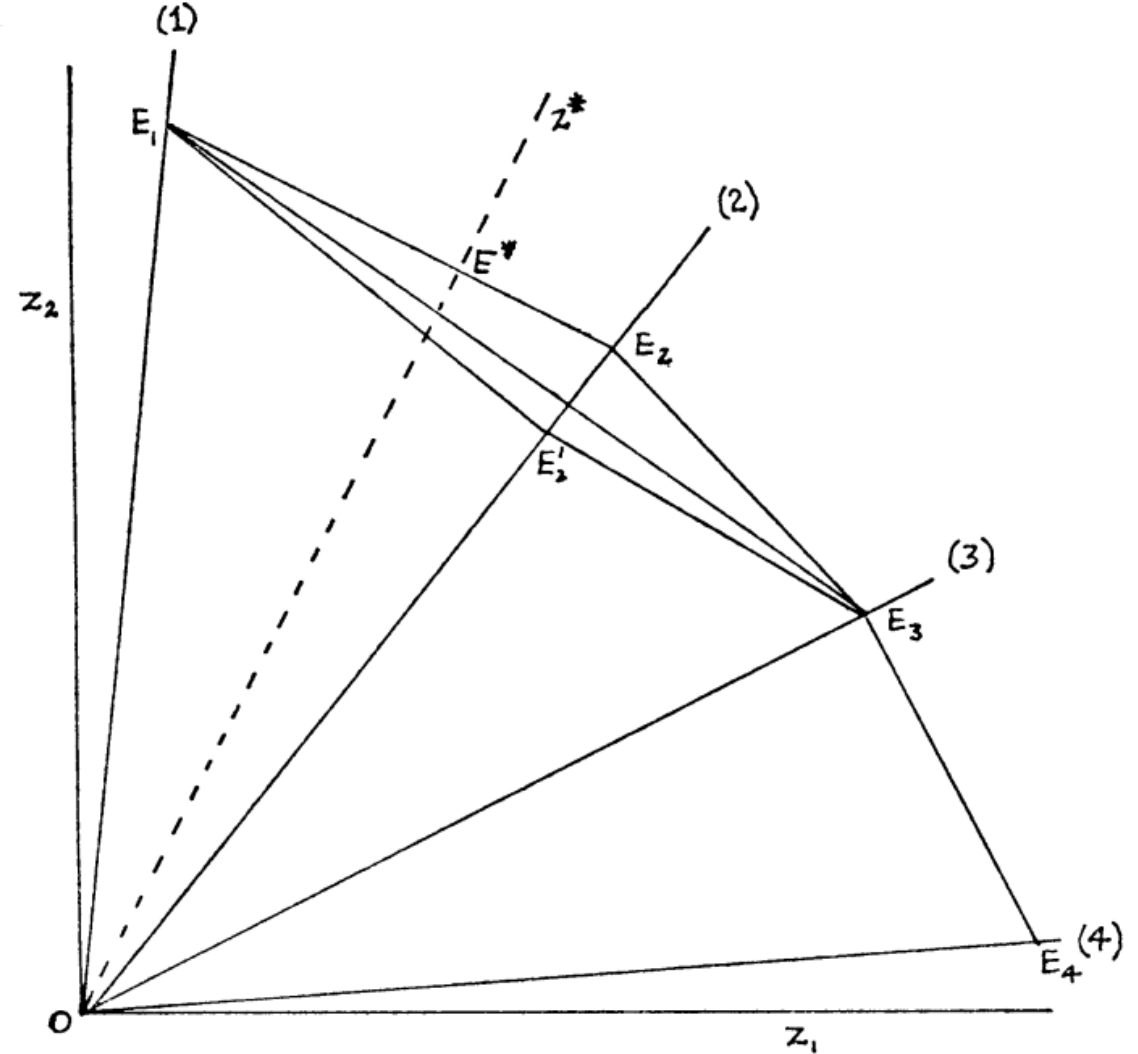


FIG. 2

Hedonic Price Theory

Rosen (1974) –
Hedonic Prices and Implicit Markets,
Product Differentiation in Pure Competition

1. Products are objectively measured in characteristics

Hedonic Price Theory

Rosen (1974) –
Hedonic Prices and Implicit Markets,
Product Differentiation in Pure Competition

1. Products are objectively measured in characteristics
2. Observed prices, combined with the set of characteristics, define a set of implicit or “hedonic” prices

Hedonic Price Theory

Rosen (1974) –
Hedonic Prices and Implicit Markets,
Product Differentiation in Pure Competition

1. Products are objectively measured in characteristics
2. Observed prices, combined with the set of characteristics, define a set of implicit or “hedonic” prices
3. This theory guides both producers *and* consumers in **characteristics space**

HEDONIC PRICES

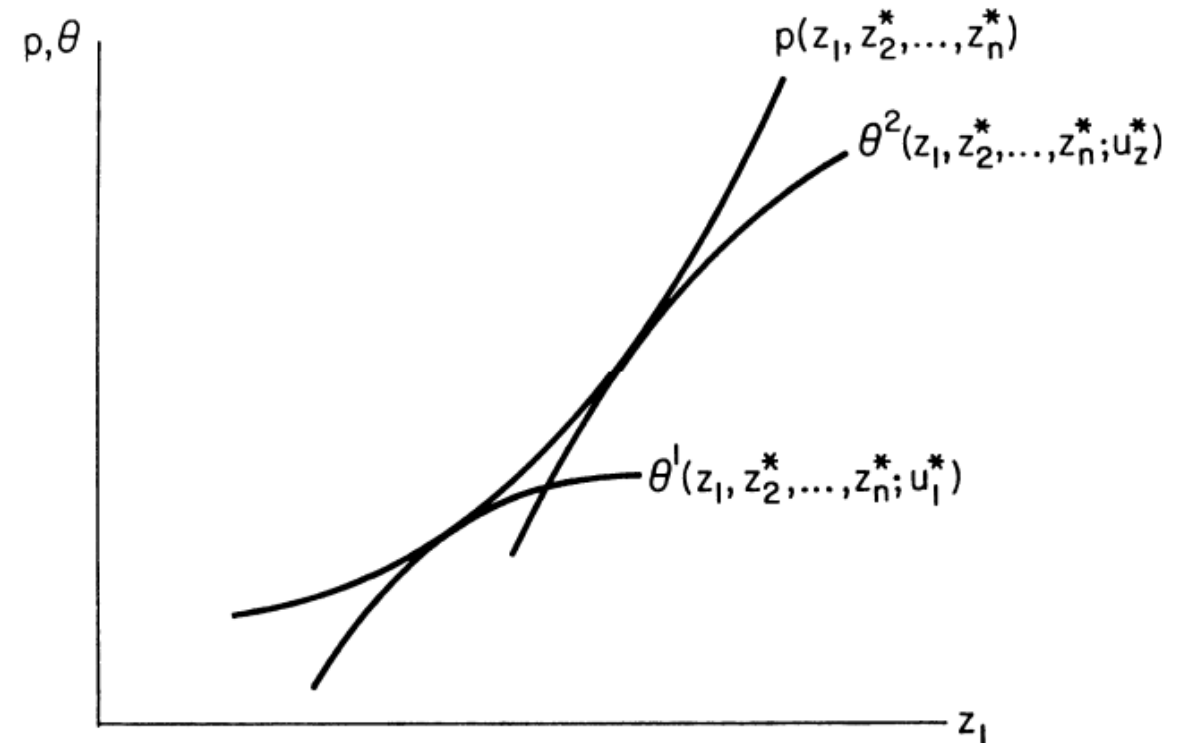
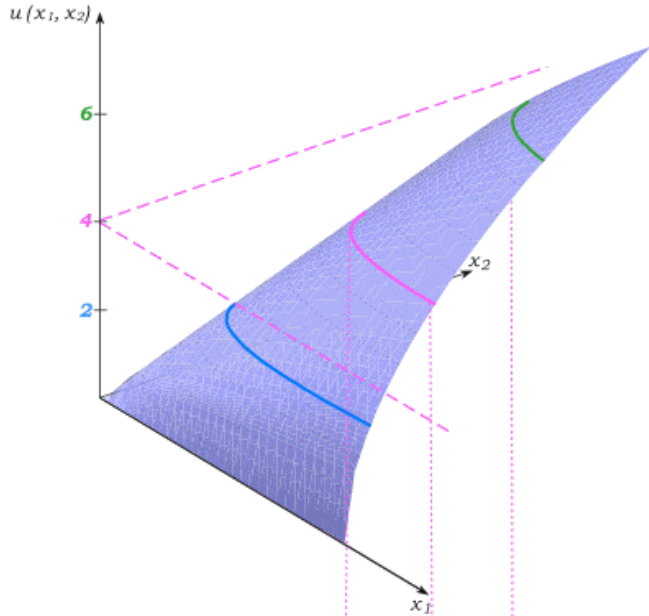


FIG. 1

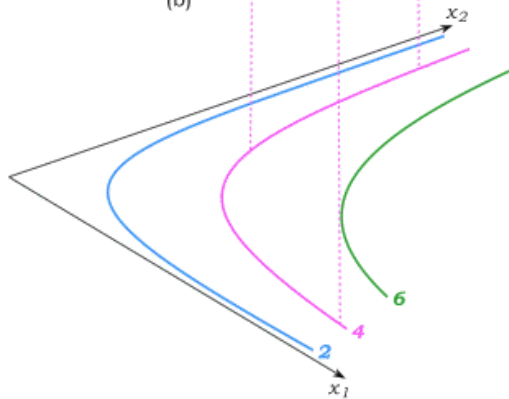
Aside: Level sets, utility, and attribute space

$$u(x_1, x_2) = x_1^{1/2} x_2^{1/2}$$

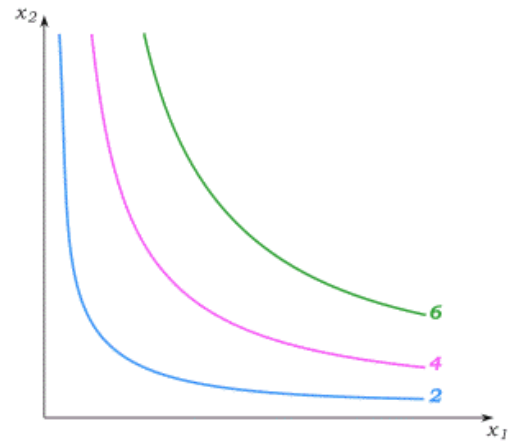
(a)



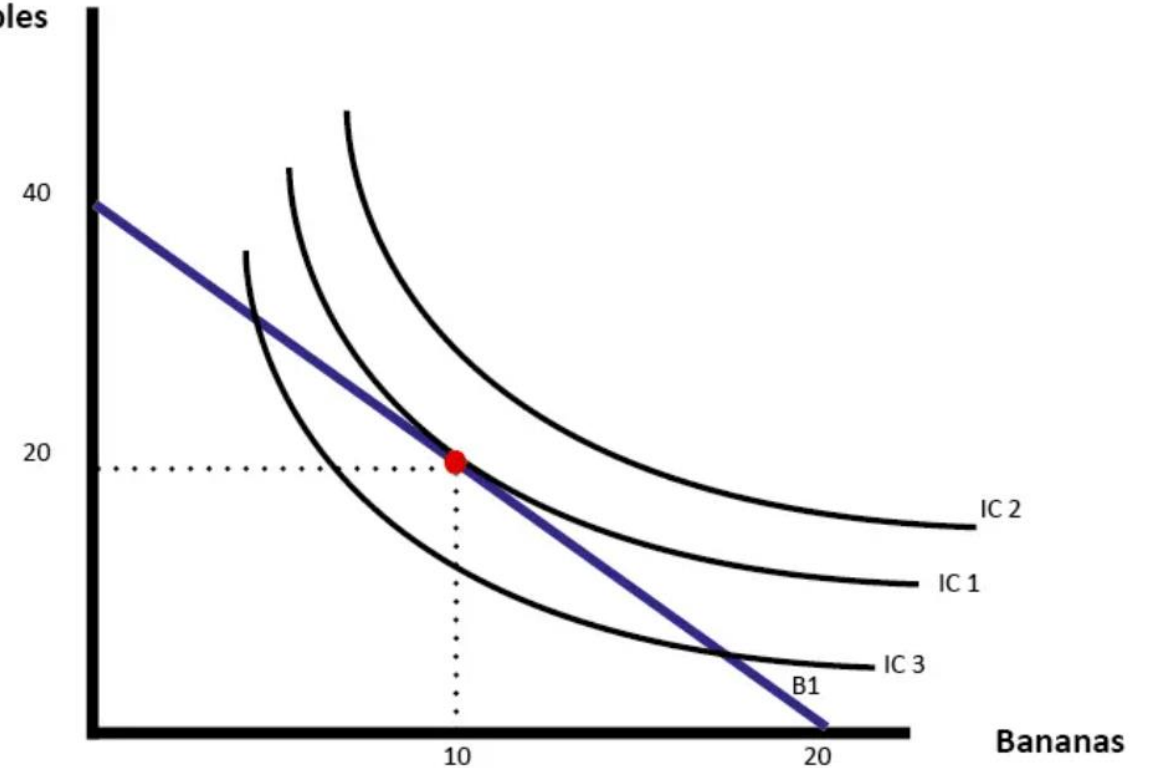
(b)



(c)



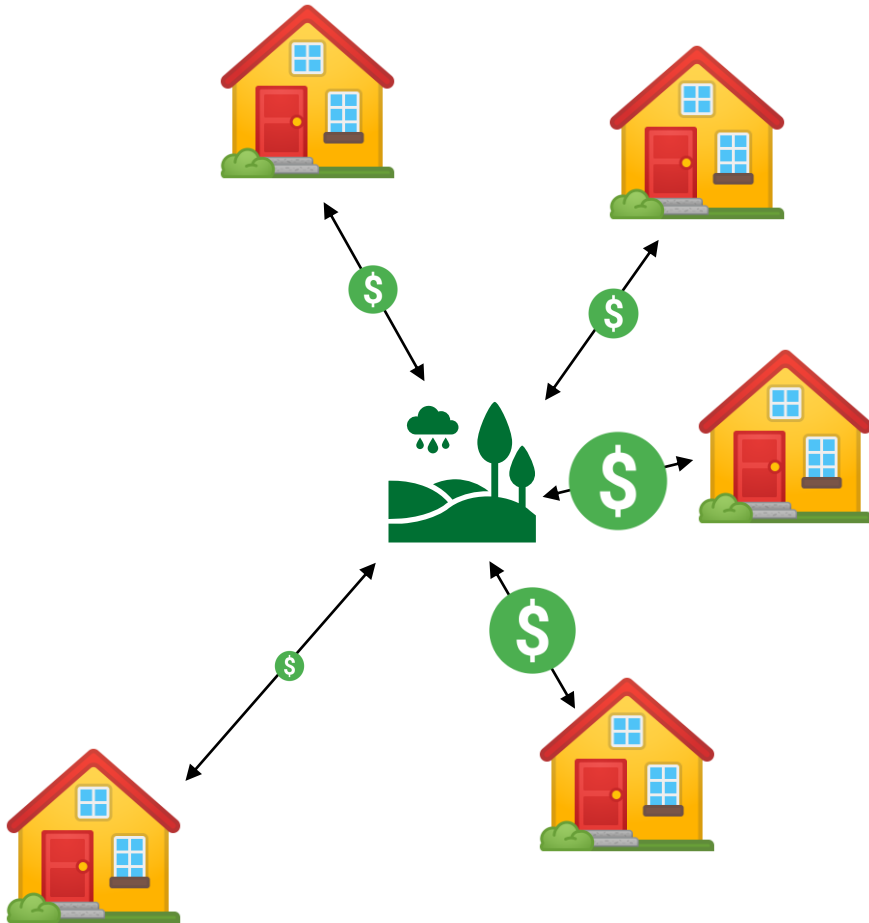
Apples



The Hedonic Price Model

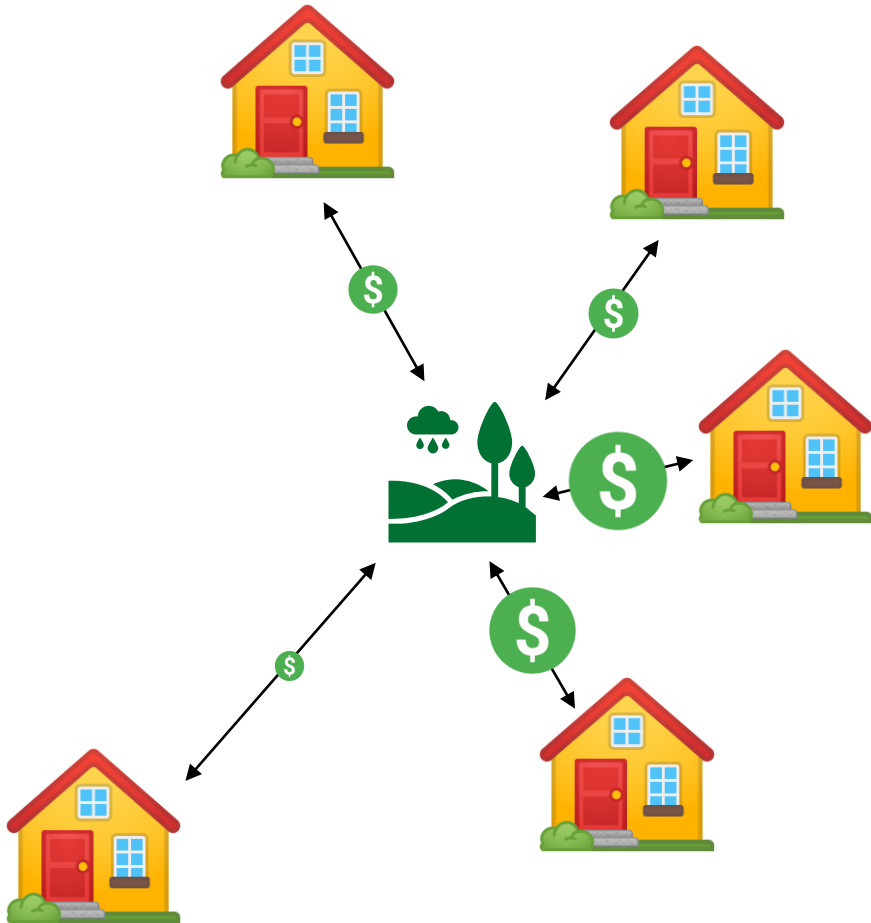
$$\text{Price}_{ijt} = \beta X + \phi + \varepsilon_{ijt}$$

- The housing market is a useful tool to estimate the value of nonmarket goods and services.



The Hedonic Price Model

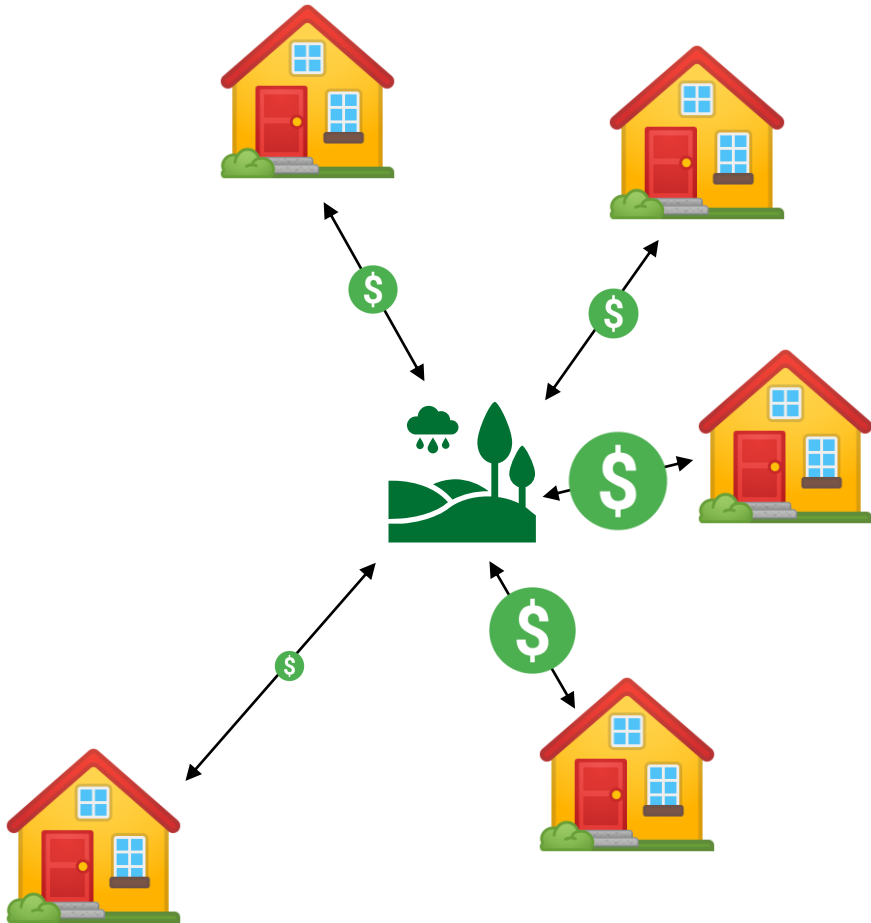
$$\text{Price}_{ijt} = \beta X + \phi + \varepsilon_{ijt}$$



- The housing market is a useful tool to estimate the value of nonmarket goods and services.
- Can be a cross-section (e.g., one observation per home, or maybe one year, etc.) or panel (e.g., observe a home sell more than once, multiple years of data, etc.).

The Hedonic Price Model

$$\text{Price}_{ijt} = \beta X + \phi + \varepsilon_{ijt}$$

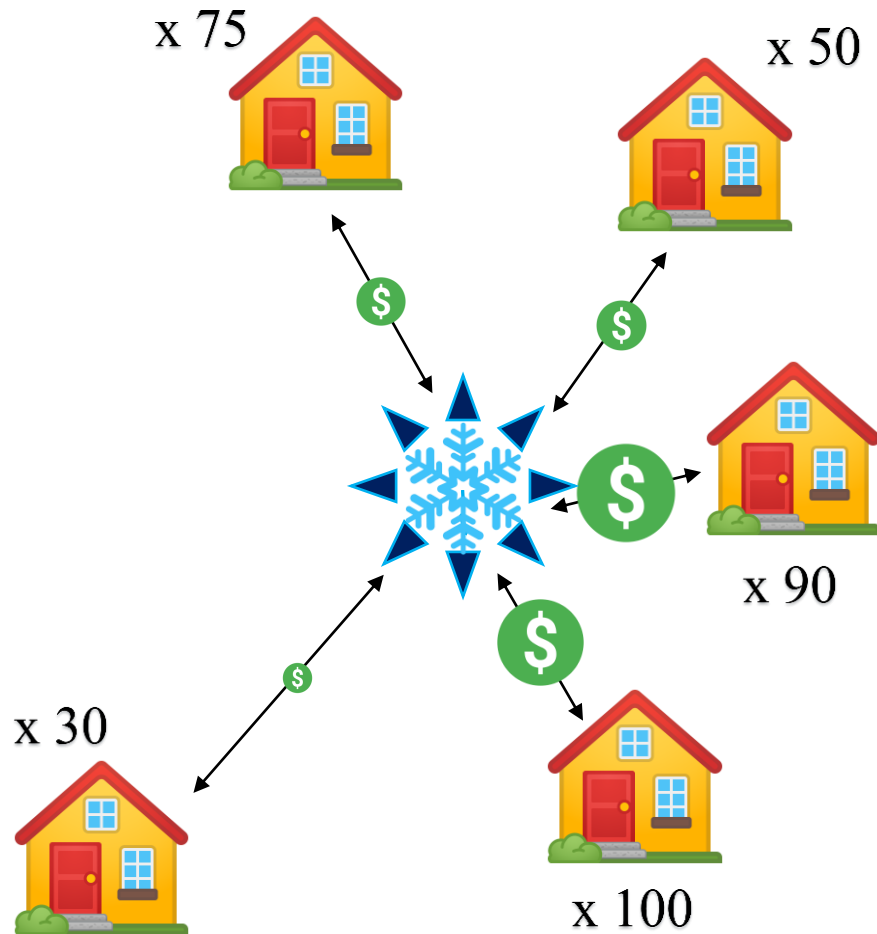


- The housing market is a useful tool to estimate the value of nonmarket goods and services.
- Can be a cross-section (e.g., one observation per home, or maybe one year, etc.) or panel (e.g., observe a home sell more than once, multiple years of data, etc.).
- By incorporating distance to an amenity as a characteristic/attribute of the home, it's possible to identify the relationship between home prices and the nonmarket amenity.

The Hedonic Price Model

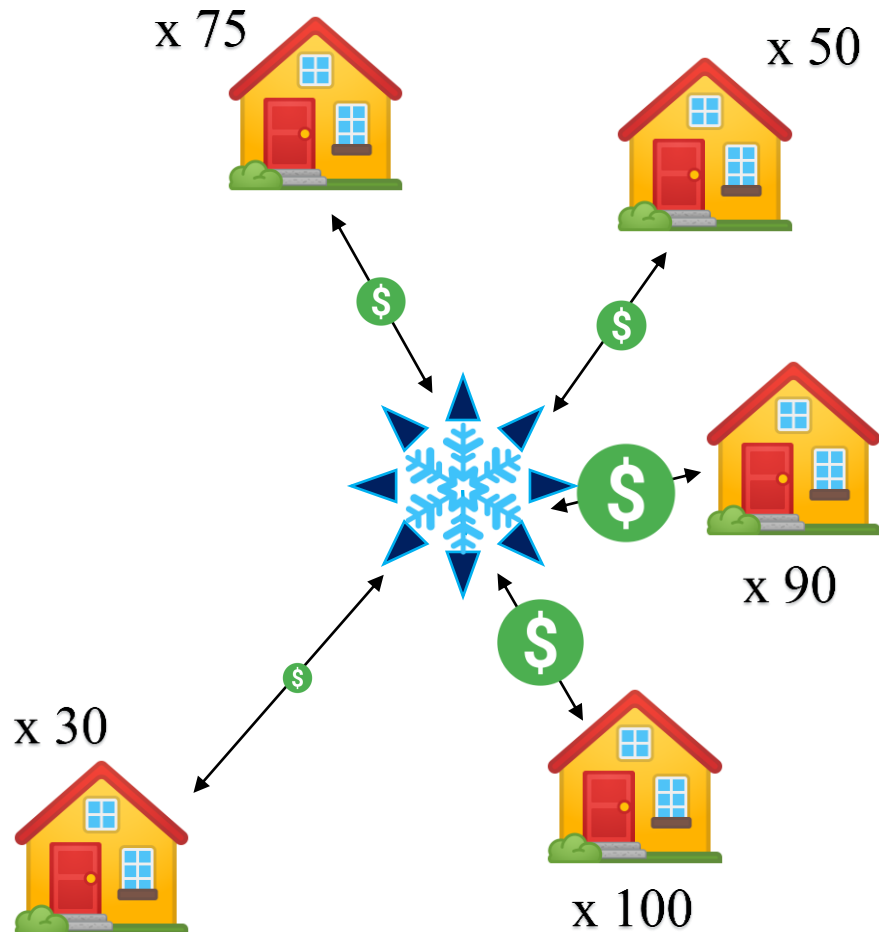
$$\text{Price}_{ijt} = \beta X + \phi + \varepsilon_{ijt}$$

- If we observe a home sell more than once, it can help control for unobservable characteristics of the home, neighborhood, etc.



The Hedonic Price Model

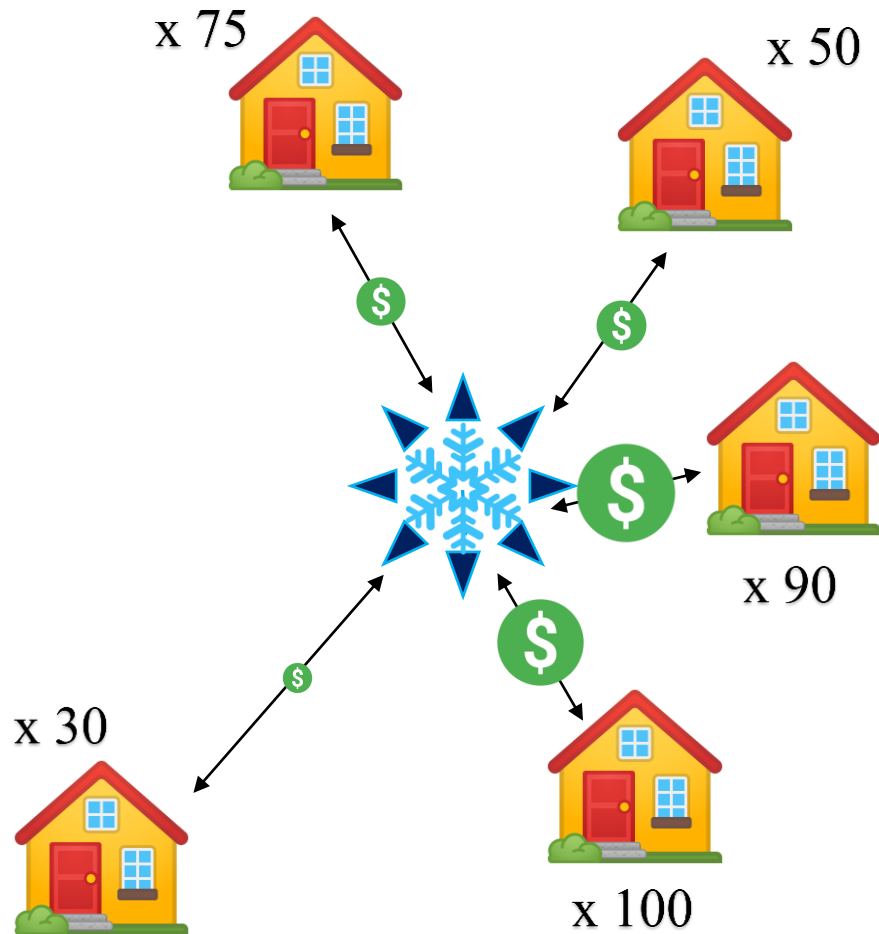
$$\text{Price}_{ijt} = \beta X + \phi + \varepsilon_{ijt}$$



- If we observe a home sell more than once, it can help control for unobservable characteristics of the home, neighborhood, etc.
- A panel of home sales can also offer an opportunity to exploit changes in environmental quality or quantity (intensive margin).

The Hedonic Price Model

$$\text{Price}_{ijt} = \beta X + \phi + \varepsilon_{ijt}$$



- If we observe a home sell more than once, it can help control for unobservable characteristics of the home, neighborhood, etc.
- A panel of home sales can also offer an opportunity to exploit changes in environmental quality or quantity (intensive margin).
- The β 's in the model (regressing price on characteristics) can be interpreted as the marginal willingness to pay for the attribute.
- [Parthum and Christensen \(2022\)](#) as an example.

A more comprehensive estimate of the value of water quality([here](#))

By: Kuwayama et al. (2022)

- Research Questions:
 1. What is the value of changes to water quality in Tampa Bay, Florida?
 2. Do conventional hedonic estimates misestimate values, and can incorporating a travel cost model improve benefits estimation?

A more comprehensive estimate of the value of water quality([here](#))

By: Kuwayama et al. (2022)

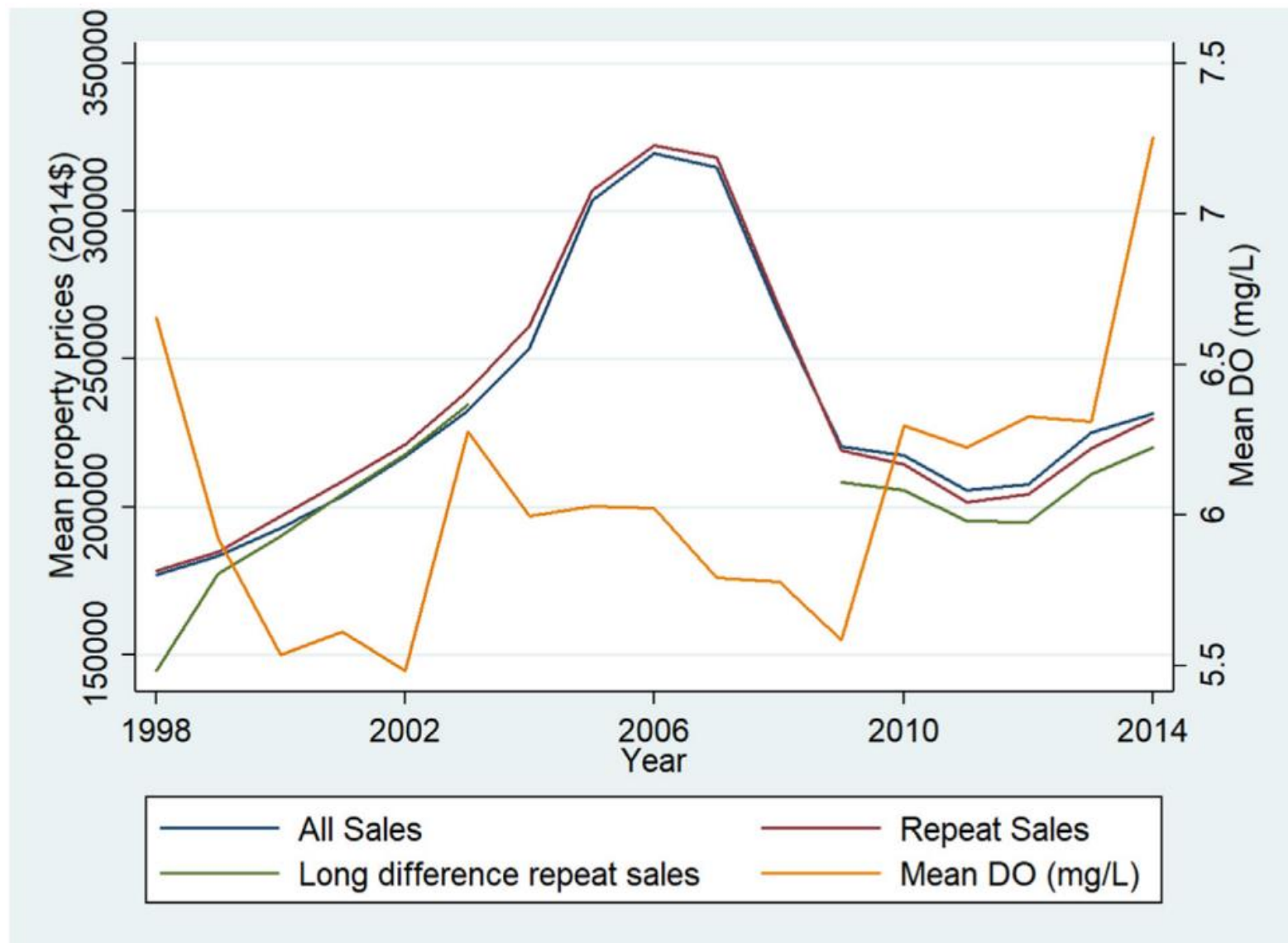
- Research Questions:
 1. What is the value of changes to water quality in Tampa Bay, Florida?
 - \$454-\$980 per household, \$366m-\$789m in the metro area per year
 2. Do conventional hedonic estimates misestimate values, and can incorporating a travel cost model improve benefits estimation?
 - The authors argue that their two-stage estimation procedure, that explicitly incorporates the recreation demand model into their hedonic estimation, significantly improves the welfare estimates of changes in water quality in the Tampa Bay area.

A more comprehensive estimate of the value of water quality([here](#))

By: Kuwayama et al. (2022)

- Data:
 1. 146k home sales between 1998 and 2014
 2. Time series of water quality data, namely dissolved oxygen
 3. Fishing survey data from the Marine Recreational Fisheries Statistics Survey (MRFSS) and the Marine Recreational Information Program (MRIP)

The Data



The Problem

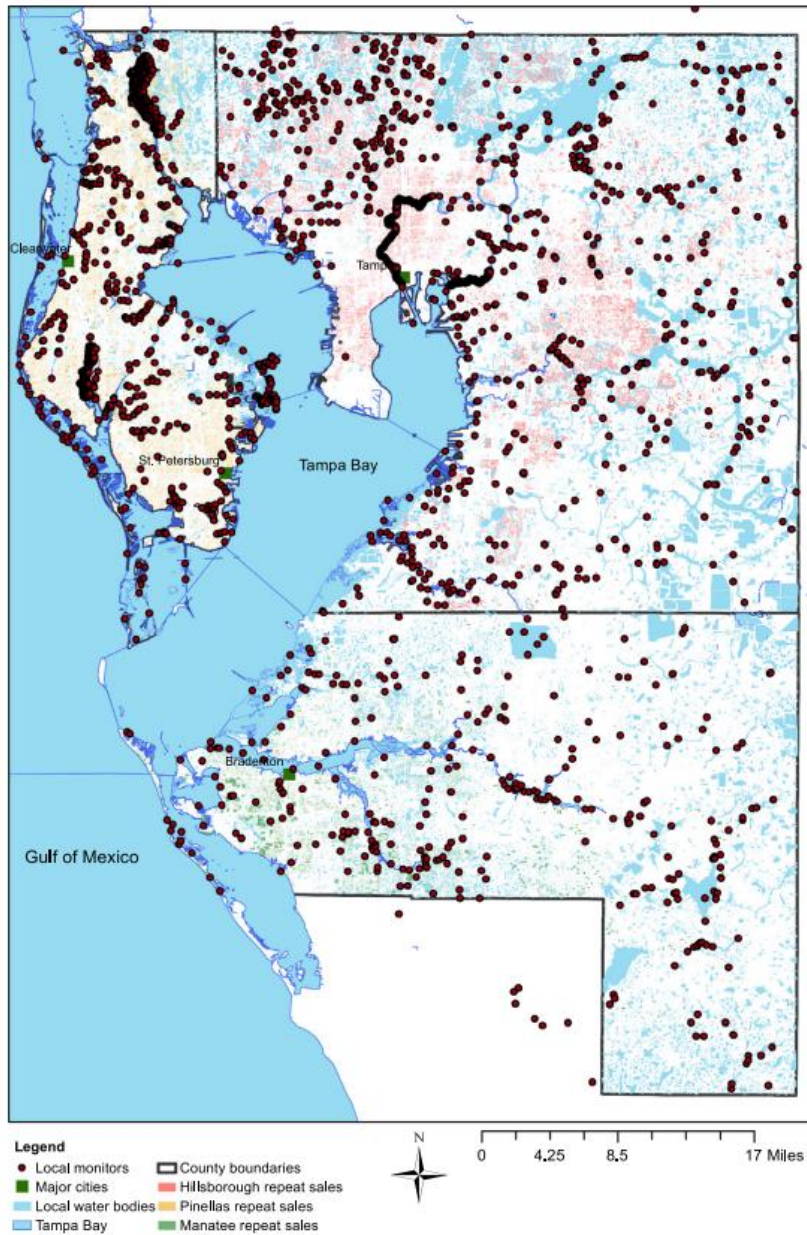
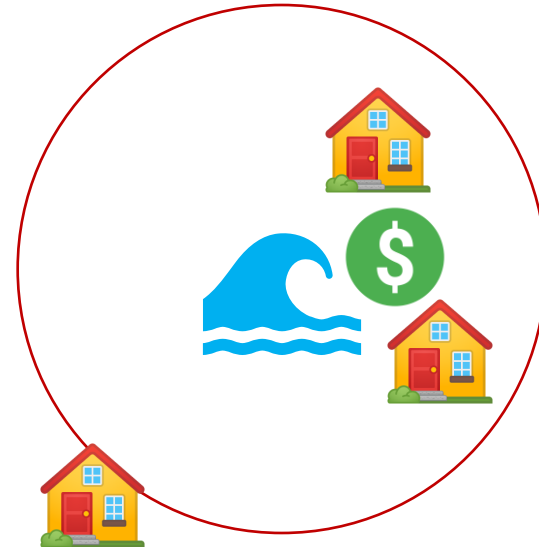


Fig. 2. Map of study area: Tampa Bay watershed, Florida.



The Problem

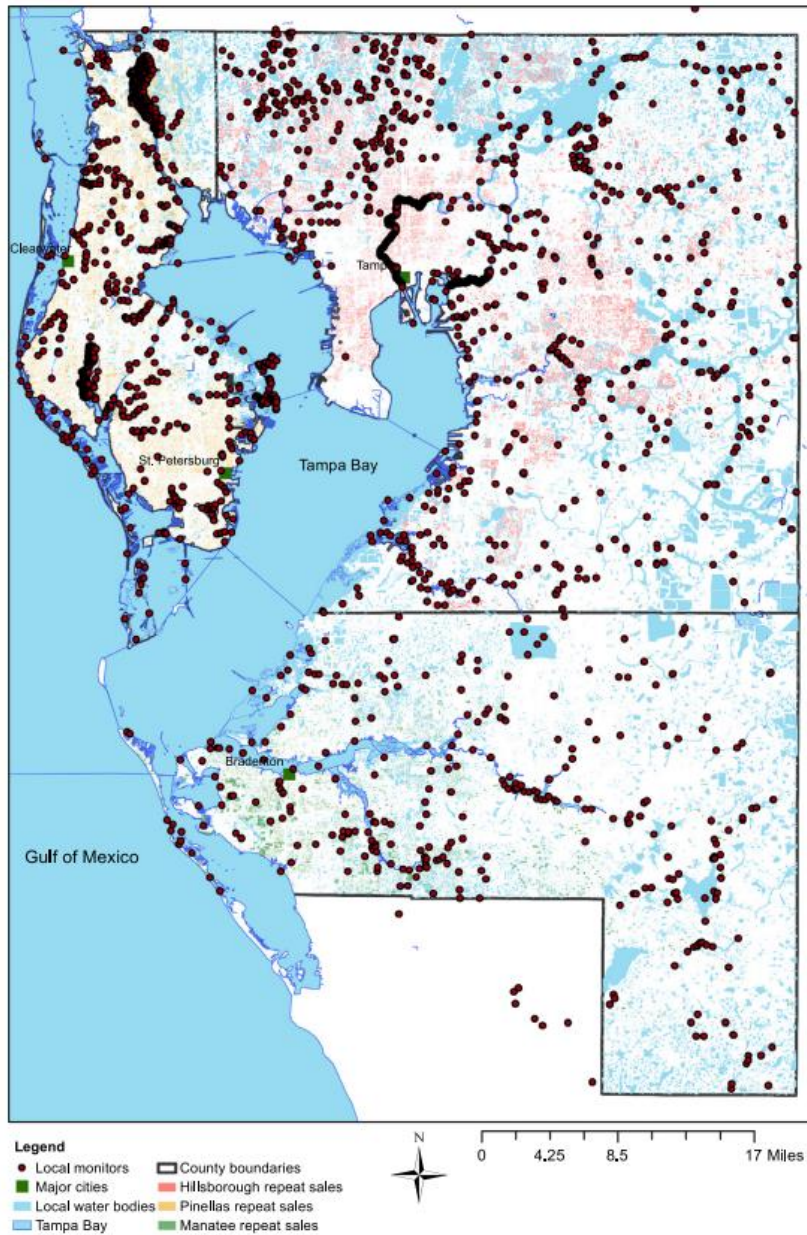


Fig. 2. Map of study area: Tampa Bay watershed, Florida.



The Problem

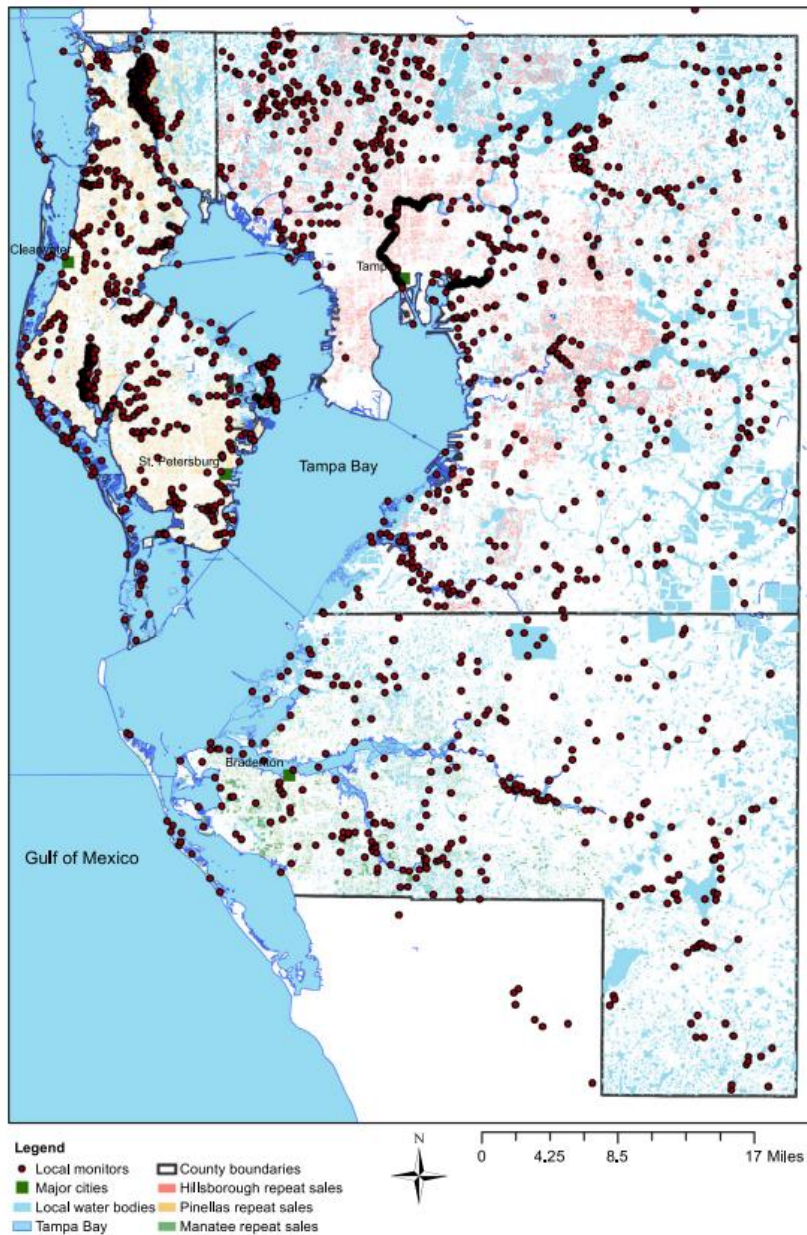
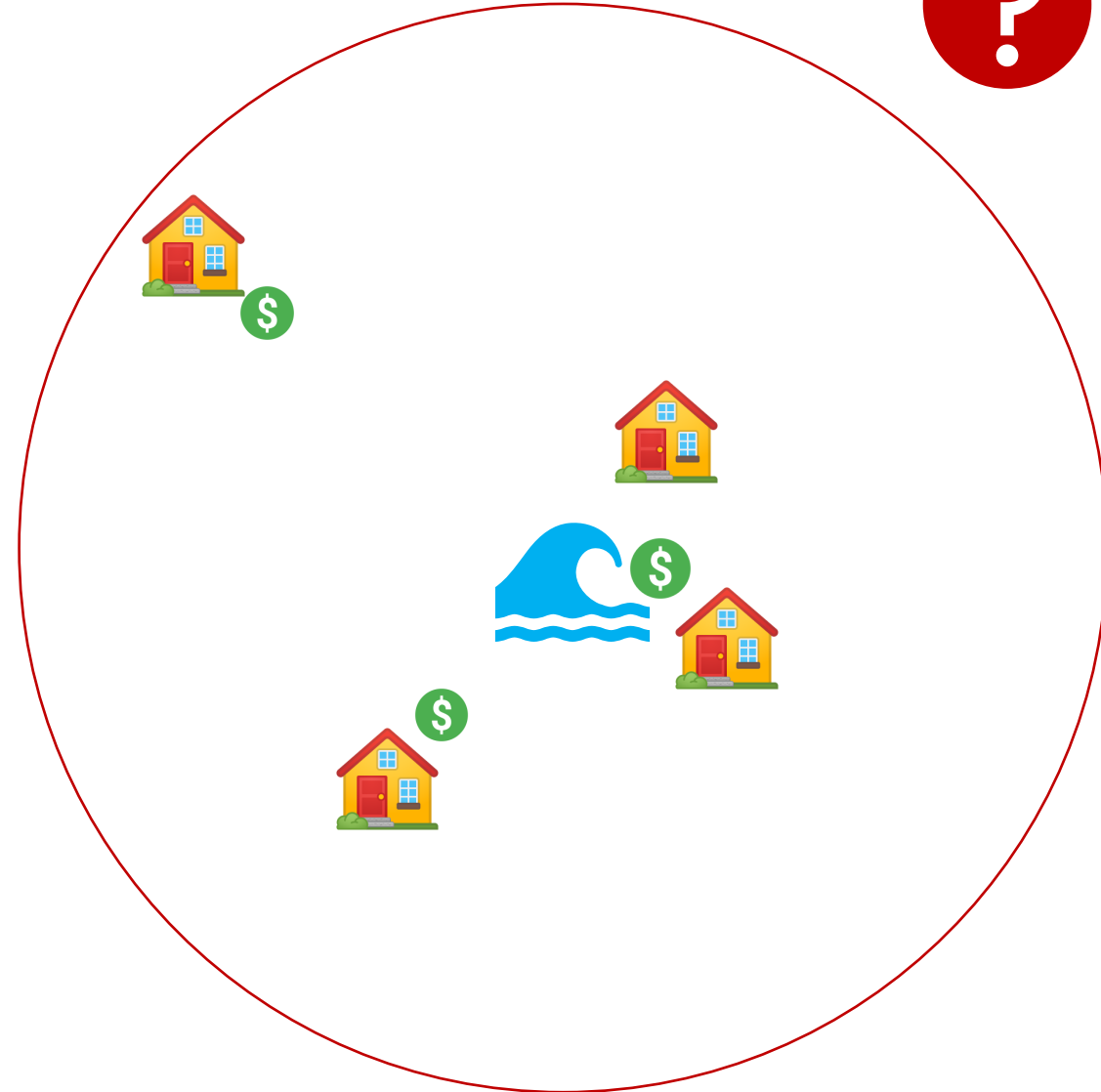


Fig. 2. Map of study area: Tampa Bay watershed, Florida.

The two-stage model

$$\log(\text{price})_{ijt} = \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \log(WQ)_{it} + \beta_3 \widehat{ECS}_{jt} + \alpha_i + \gamma_t + \omega_m + \varepsilon_{ijt}$$

The two-stage model

$$\log(\text{price})_{ijt} = \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \log(WQ)_{it} + \boxed{\beta_3 \widehat{ECS}_{jt}} + \alpha_i + \gamma_t + \omega_m + \varepsilon_{ijt}$$

The two-stage model

$$\log(\text{price})_{ijt} = \beta_0 + \beta_1 \text{Age}_{it} + \boxed{\beta_2} \log(WQ)_{it} + \beta_3 \widehat{ECS}_{jt} + \alpha_i + \gamma_t + \omega_m + \varepsilon_{ijt}$$

The two-stage model

$$\log(\text{price})_{ijt} = \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \log(WQ)_{it} + \beta_3 \widehat{ECS}_{jt} + \alpha_i + \gamma_t + \omega_m + \varepsilon_{ijt}$$

where

$$\widehat{ECS}_{jt} = N_{jt}^{-1} \sum_{i=1}^{N_{jt}} E(CS)_{it}$$

The two-stage model

$$\log(\text{price})_{ijt} = \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \log(WQ)_{it} + \beta_3 \widehat{ECS}_{jt} + \alpha_i + \gamma_t + \omega_m + \varepsilon_{ijt}$$

where

$$\widehat{ECS}_{jt} = N_{jt}^{-1} \sum_{i=1}^{N_{jt}} E(CS)_{it}$$

and

$$E(CS)_{it} = \frac{EV_{it}}{\alpha_1}$$

The two-stage model

$$\log(\text{price})_{ijt} = \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \log(WQ)_{it} + \beta_3 \widehat{ECS}_{jt} + \alpha_i + \gamma_t + \omega_m + \varepsilon_{ijt}$$

where

$$\widehat{ECS}_{jt} = N_{jt}^{-1} \sum_{i=1}^{N_{jt}} E(CS)_{it}$$

and

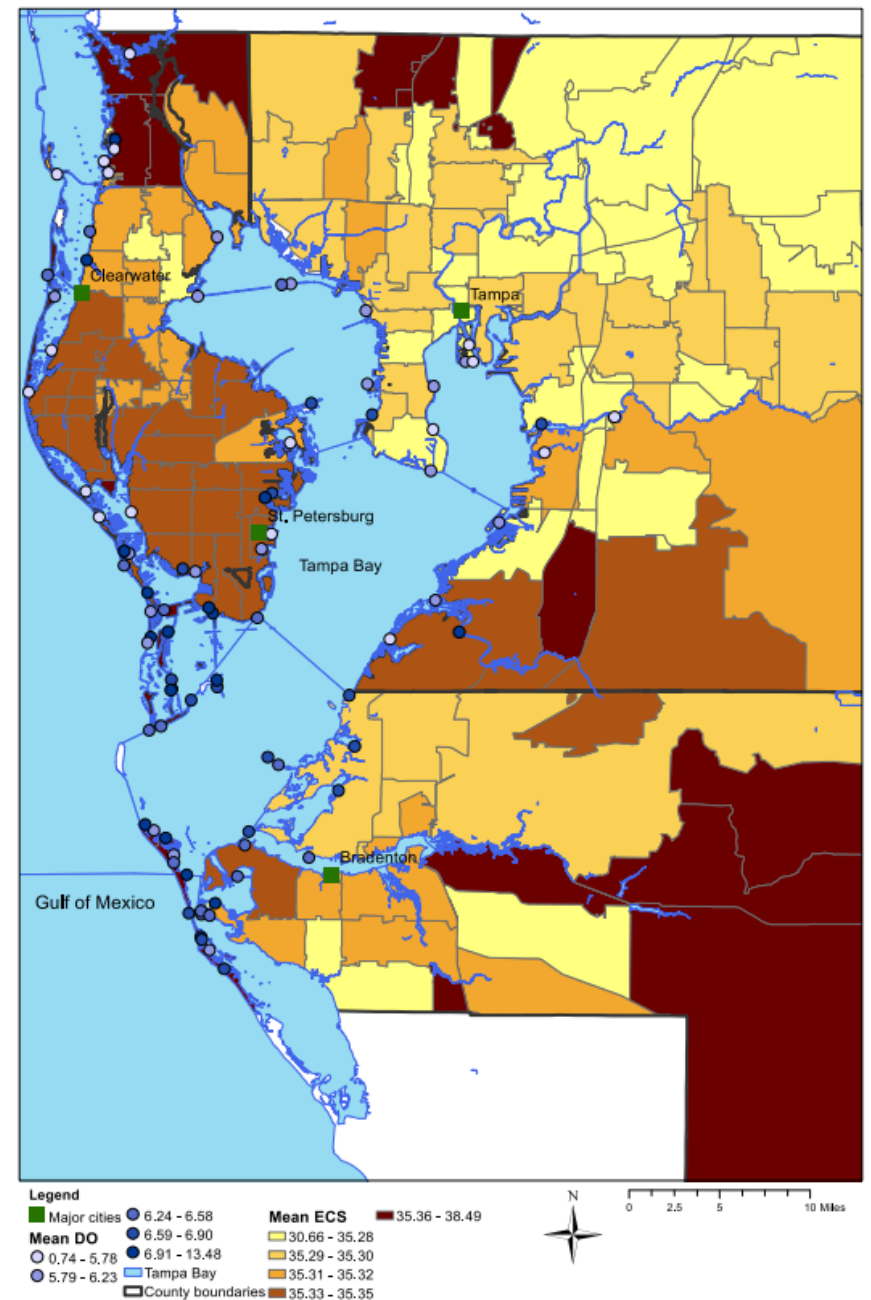
$$E(CS)_{it} = \frac{EV_{it}}{\alpha_1}$$

and

$$EV_{it} = \log \left(\sum_{k=1}^K \exp(\hat{V}_{ikt}) \right)$$

$$\widehat{ECS}_{jt} = N_{jt}^{-1} \sum_{i=1}^{N_{jt}} E(CS)_{it}$$

- Lots of variation across space (zip codes)
- Some of the largest estimates of consumer surplus are estimated to be further inland.
- This suggests that a simple radius and hedonic approach would likely miss out on a lot of potential benefits



$$\log(\text{price})_{ijt} = \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \log(WQ)_{it} + \beta_3 \widehat{ECS}_{jt} + \alpha_i + \gamma_t + \omega_m + \varepsilon_{ijt}$$

Table 4

Second-stage hedonic regression results for the property fixed effects model.

	(1) Basic 3 km	(2) No ECS_{jt} 3 km	(3) Basic 5 km	(4) County time trend	(5) Subdiv. time trend
$\ln(\text{DO})$	0.0116*** (0.00306)	0.0113*** (0.00306)	0.0129*** (0.00442)	0.0111*** (0.00318)	0.00967*** (0.00340)
ECS_{jt}	0.251*** (0.0814)		0.0165 (0.0771)	0.0609 (0.0795)	0.0272 (0.0846)
Property age	-0.0123*** (0.00328)	-0.0123*** (0.00328)	0.0112 (0.00822)	-0.0135*** (0.00326)	-0.0139*** (0.00336)
Property FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Sale month FE	Yes	Yes	Yes	Yes	Yes
County-year trend	No	No	No	Yes	No
Subdivision-year trend	No	No	No	No	Yes
Observations	146,903	146,903	166,706	146,903	125,276
R-squared	0.627	0.627	0.661	0.633	0.632
MWTP for 1 mg/L local DO (\$)	459	448	516	440	383
MWTP for 1 mg/L Tampa Bay DO (\$)	37,769	N/A	2,483	9,164	4,093

Estimated standard errors in parentheses are clustered by property.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the log property transaction price. Column 1 uses a 3-km radius to define average water quality around properties. Column 2 drops the recreational utility index, ECS_{jt} . Column 3 repeats Column 1, using a 5-km instead of a 3-km radius to define average water quality around properties. N rises in Column 3 because more repeat sales are located within 5 km of at least one water quality monitor than within 3 km. Column 4 includes county-specific trends as additional controls. Column 5 includes census subdivision-specific trends. Reported coefficient estimates and standard errors are obtained using multiple imputation, using methods described in detail in Section 5.2.1.

$$\log(\text{price})_{ijt} = \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \log(WQ)_{it} + \beta_3 \widehat{ECS}_{jt} + \alpha_i + \gamma_t + \omega_m + \varepsilon_{ijt}$$

Table 4

Second-stage hedonic regression results for the property fixed effects model.

	(1) Basic 3 km	(2) No ECS_{jt} 3 km	(3) Basic 5 km	(4) County time trend	(5) Subdiv. time trend
$\ln(\text{DO})$	0.0116*** (0.00306)	0.0113*** (0.00306)	0.0129*** (0.00442)	0.0111*** (0.00318)	0.00967*** (0.00340)
ECS_{jt}	0.251*** (0.0814)		0.0165 (0.0771)	0.0609 (0.0795)	0.0272 (0.0846)
Property age	-0.0123*** (0.00328)	-0.0123*** (0.00328)	0.0112 (0.00822)	-0.0135*** (0.00326)	-0.0139*** (0.00336)
Property FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Sale month FE	Yes	Yes	Yes	Yes	Yes
County-year trend	No	No	No	Yes	No
Subdivision-year trend	No	No	No	No	Yes
Observations	146,903	146,903	166,706	146,903	125,276
R-squared	0.627	0.627	0.661	0.633	0.632
MWTP for 1 mg/L local DO (\$)	459	448	516	440	383
MWTP for 1 mg/L Tampa Bay DO (\$)	37,769	N/A	2,483	9,164	4,093

Estimated standard errors in parentheses are clustered by property.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the log property transaction price. Column 1 uses a 3-km radius to define average water quality around properties. Column 2 drops the recreational utility index, ECS_{jt} . Column 3 repeats Column 1, using a 5-km instead of a 3-km radius to define average water quality around properties. N rises in Column 3 because more repeat sales are located within 5 km of at least one water quality monitor than within 3 km. Column 4 includes county-specific trends as additional controls. Column 5 includes census subdivision-specific trends. Reported coefficient estimates and standard errors are obtained using multiple imputation, using methods described in detail in Section 5.2.1.

Careful exploration of potential confounders:

“One caveat of our property transaction data is that we do not observe changes in property characteristics over time (except age, which we construct from the year each home was built). If the likelihood of renovation is correlated with either local water quality improvements or the recreational benefits of regional water quality improvements, this omission could bias our estimates (Billings, 2015). If households substitute structural improvements for neighborhood quality, this bias would be negative. If neighborhood quality spurs home improvements (for example, if water quality improvements lead to gentrification), the bias would be upward. Incorporating renovation information, for example from residential construction permitting data, into hedonic analyses that value environmental amenities is an important area for future work.”

Careful exploration of potential confounders:

“One caveat of our property transaction data is that we do not observe changes in property characteristics over time (except age, which we construct from the year each home was built). If the likelihood of renovation is correlated with either local water quality improvements or the recreational benefits of regional water quality improvements, this omission could bias our estimates (Billings, 2015). If households substitute structural improvements for neighborhood quality, this bias would be negative. If neighborhood quality spurs home improvements (for example, if water quality improvements lead to gentrification), the bias would be upward. Incorporating renovation information, for example from residential construction permitting data, into hedonic analyses that value environmental amenities is an important area for future work.”

Careful exploration of potential confounders:

“One caveat of our property transaction data is that we do not observe changes in property characteristics over time (except age, which we construct from the year each home was built). If the likelihood of renovation is correlated with either local water quality improvements or the recreational benefits of regional water quality improvements, this omission could bias our estimates (Billings, 2015). If households substitute structural improvements for neighborhood quality, this bias would be negative. If neighborhood quality spurs home improvements (for example, if water quality improvements lead to gentrification), the bias would be upward. Incorporating renovation information, for example from residential construction permitting data, into hedonic analyses that value environmental amenities is an important area for future work.”

Sorting or Steering: The effects of housing discrimination on neighborhood choice ([here](#))

By: Christensen and Timmins (NBER 2022)

- Research Questions:
 1. Can people simply “vote with their feet”?

Sorting or Steering: The effects of housing discrimination on neighborhood choice ([here](#))

By: Christensen and Timmins (NBER 2022)

Growing evidence indicates that neighborhoods affect human capital accumulation, raising concern that the exclusionary effects of housing discrimination could contribute to persistent inequality. Using data from HUD's most recent Housing Discrimination Study and micro-level data on key attributes of neighborhoods in 28 US cities, we find strong evidence that discrimination constrains the neighborhood choices of minorities in a housing search. Minority testers are significantly more likely to be steered towards neighborhoods with lower quality schools and neighborhood human capital, and higher rates of assault and pollution exposure. Holding location preferences and income constant, discriminatory steering alone can explain a disproportionate number of minority households found in high poverty neighborhoods in the United States and could contribute to racial gaps in inter-generational income mobility. These results have important implications for the analysis of neighborhood effects and further establish discrimination as a mechanism underlying observed correlations between race and pollution exposures.

Sorting or Steering: The effects of housing discrimination on neighborhood choice ([here](#))

By: Christensen and Timmins (NBER 2022)

Growing evidence indicates that neighborhoods affect human capital accumulation, raising concern that the exclusionary effects of housing discrimination could contribute to persistent inequality. Using data from HUD's most recent Housing Discrimination Study and micro-level data on key attributes of neighborhoods in 28 US cities, we find strong evidence that discrimination constrains the neighborhood choices of minorities in a housing search. Minority testers are significantly more likely to be steered towards neighborhoods with lower quality schools and neighborhood human capital, and higher rates of assault and pollution exposure. Holding location preferences and income constant, discriminatory steering alone can explain a disproportionate number of minority households found in high poverty neighborhoods in the United States and could contribute to racial gaps in inter-generational income mobility. These results have important implications for the analysis of neighborhood effects and further establish discrimination as a mechanism underlying observed correlations between race and pollution exposures.

Sorting or Steering: The effects of housing discrimination on neighborhood choice ([here](#))

By: Christensen and Timmins (NBER 2022)

Growing evidence indicates that neighborhoods affect human capital accumulation, raising concern that the exclusionary effects of housing discrimination could contribute to persistent inequality. Using data from HUD's most recent Housing Discrimination Study and micro-level data on key attributes of neighborhoods in 28 US cities, we find strong evidence that discrimination constrains the neighborhood choices of minorities in a housing search. Minority testers are significantly more likely to be steered towards neighborhoods with lower quality schools and neighborhood human capital, and higher rates of assault and pollution exposure. Holding location preferences and income constant, discriminatory steering alone can explain a disproportionate number of minority households found in high poverty neighborhoods in the United States and could contribute to racial gaps in inter-generational income mobility. These results have important implications for the analysis of neighborhood effects and further establish discrimination as a mechanism underlying observed correlations between race and pollution exposures.

Sorting or Steering: The effects of housing discrimination on neighborhood choice ([here](#))

By: Christensen and Timmins (NBER 2022)

Growing evidence indicates that neighborhoods affect human capital accumulation, raising concern that the exclusionary effects of housing discrimination could contribute to persistent inequality. Using data from HUD's most recent Housing Discrimination Study and micro-level data on key attributes of neighborhoods in 28 US cities, we find strong evidence that discrimination constrains the neighborhood choices of minorities in a housing search. Minority testers are significantly more likely to be steered towards neighborhoods with lower quality schools and neighborhood human capital, and higher rates of assault and pollution exposure. Holding location preferences and income constant, discriminatory steering alone can explain a disproportionate number of minority households found in high poverty neighborhoods in the United States and could contribute to racial gaps in inter-generational income mobility. These results have important implications for the analysis of neighborhood effects and further establish discrimination as a mechanism underlying observed correlations between race and pollution exposures.

Sorting or Steering: The effects of housing discrimination on neighborhood choice ([here](#))

By: Christensen and Timmins (NBER 2022)

Growing evidence indicates that neighborhoods affect human capital accumulation, raising concern that the exclusionary effects of housing discrimination could contribute to persistent inequality. Using data from HUD's most recent Housing Discrimination Study and micro-level data on key attributes of neighborhoods in 28 US cities, we find strong evidence that discrimination constrains the neighborhood choices of minorities in a housing search. Minority testers are significantly more likely to be steered towards neighborhoods with lower quality schools and neighborhood human capital, and higher rates of assault and pollution exposure. Holding location preferences and income constant, discriminatory steering alone can explain a disproportionate number of minority households found in high poverty neighborhoods in the United States and could contribute to racial gaps in inter-generational income mobility. These results have important implications for the analysis of neighborhood effects and further establish discrimination as a mechanism underlying observed correlations between race and pollution exposures.

Sorting or Steering: The effects of housing discrimination on neighborhood choice ([here](#))

By: Christensen and Timmins (NBER 2022)

Growing evidence indicates that neighborhoods affect human capital accumulation, raising concern that the exclusionary effects of housing discrimination could contribute to persistent inequality. Using data from HUD's most recent Housing Discrimination Study and micro-level data on key attributes of neighborhoods in 28 US cities, we find strong evidence that discrimination constrains the neighborhood choices of minorities in a housing search. Minority testers are significantly more likely to be steered towards neighborhoods with lower quality schools and neighborhood human capital, and higher rates of assault and pollution exposure. Holding location preferences and income constant, discriminatory steering alone can explain a disproportionate number of minority households found in high poverty neighborhoods in the United States and could contribute to racial gaps in inter-generational income mobility. These results have important implications for the analysis of neighborhood effects and further establish discrimination as a mechanism underlying observed correlations between race and pollution exposures.

Next class

- Stated Preferences and Hypothetical Markets:
 - [Parthum and Ando \(2020\)](#)
 - I chose this paper not because it is one of mine, but because I think I did a better job than most at walking through the intuition of the approach and various assumptions along the way.
- September 26th
 - Estimating the relationship between climate and the economy
 - We are going to hear about some of the work Yagmur (one of your amazing TA's) is doing in this realm!