HEDONIC AND SORTING MODELS FOR ENVIRONMENTAL VALUATION

Nicolai Kuminoff
(ASU Economics Department & NBER)

CAERE / SUFE Conference: May 2025

Enduring Popularity of Hedonic Property Value Models

A pure theory of local expenditures
CM **Tiebout** - Journal of political economy, 1956 - journals.uchicago.edu
NE of the most important recent developments in the area of" applied economic theory" has been the work of Musgrave and Samuelson in public finance theory. 2 The two writers agree …
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Hedonic prices and implicit markets: product differentiation in pure competition
S **Rosen** - Journal of political economy, 1974 - journals.uchicago.edu
A class of differentiated products is completely described by a vector of objectively measured characteristics. Observed product prices and the specific amounts of characteristics …
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- Intuitive and economically rich premise
- Empirically tractable
- Potential to inform public policy
- Residential location is perhaps the single most important market choice for determining consumption of environmental amenities

Enduring Popularity of Hedonic Property Value Models

There are several literature reviews:

- Palmquist's 2005 chapter in *Handbook of Environmental Economics*
- Kuminoff, Smith and Timmins (JEL 2013)
- Chapter in Freeman, Herriges and Kling's (2014) textbook
- Chapter in Phaneuf and Requate's (2017) textbook
- Taylor's (2017) chapter in *A Primer in Nonmarket Valuation*
- Bishop et al. (REEP 2020)

Today: modern techniques for environmental valuation

- High expectations for causal identification
- Subtle mapping from identified parameters to welfare measures
- Heterogeneity and distributional effects
- Frictions

Outline

1. The hedonic property value model

2. Best practices for using price functions to estimate MWTP

3. Modeling sorting behavior

   - identification and estimation

   - validation

   - extensions: dynamics, heterogeneous beliefs

4. Questions / Discussion

Slides: https://nickkuminoff.github.io/webpage/hedonic.pdf

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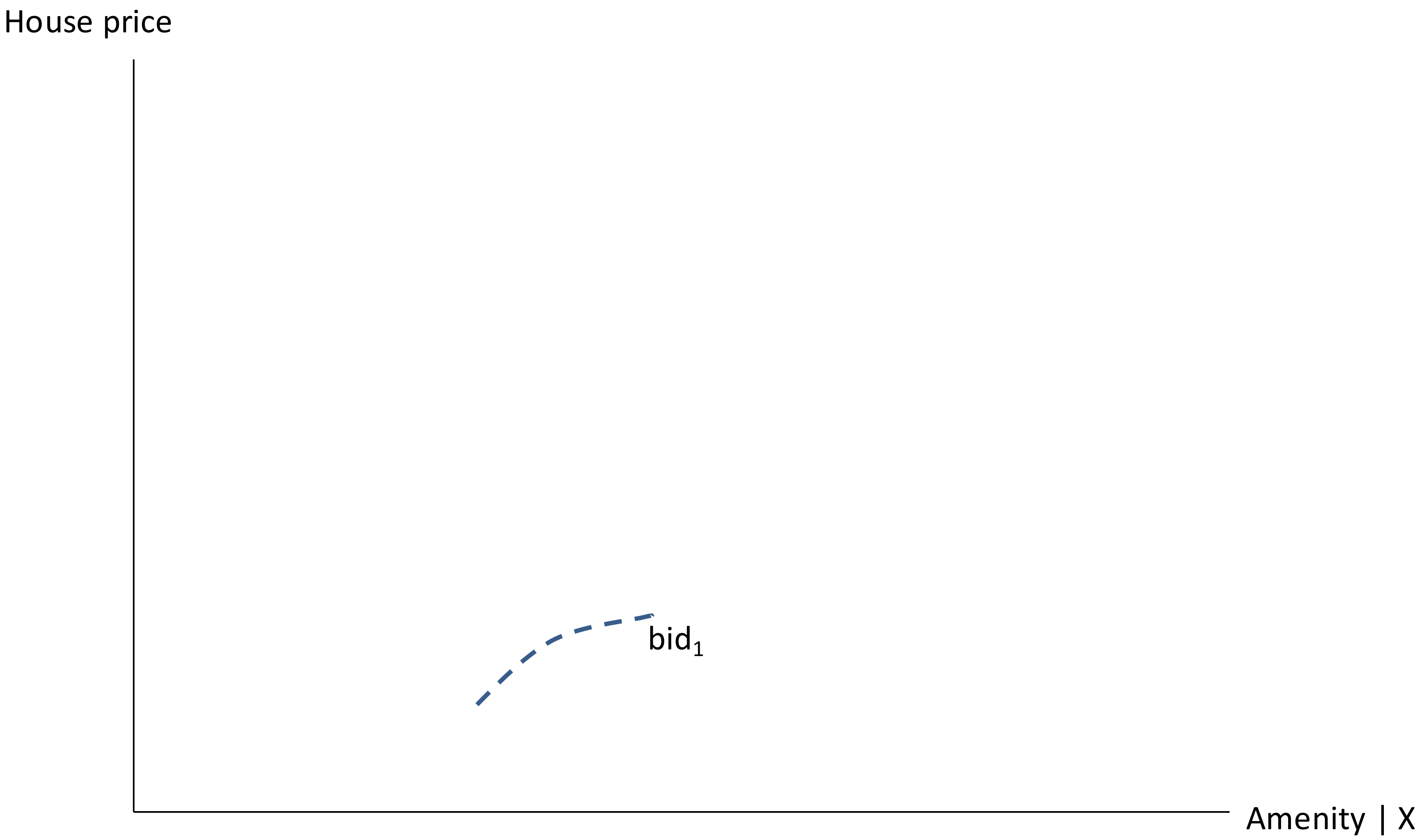
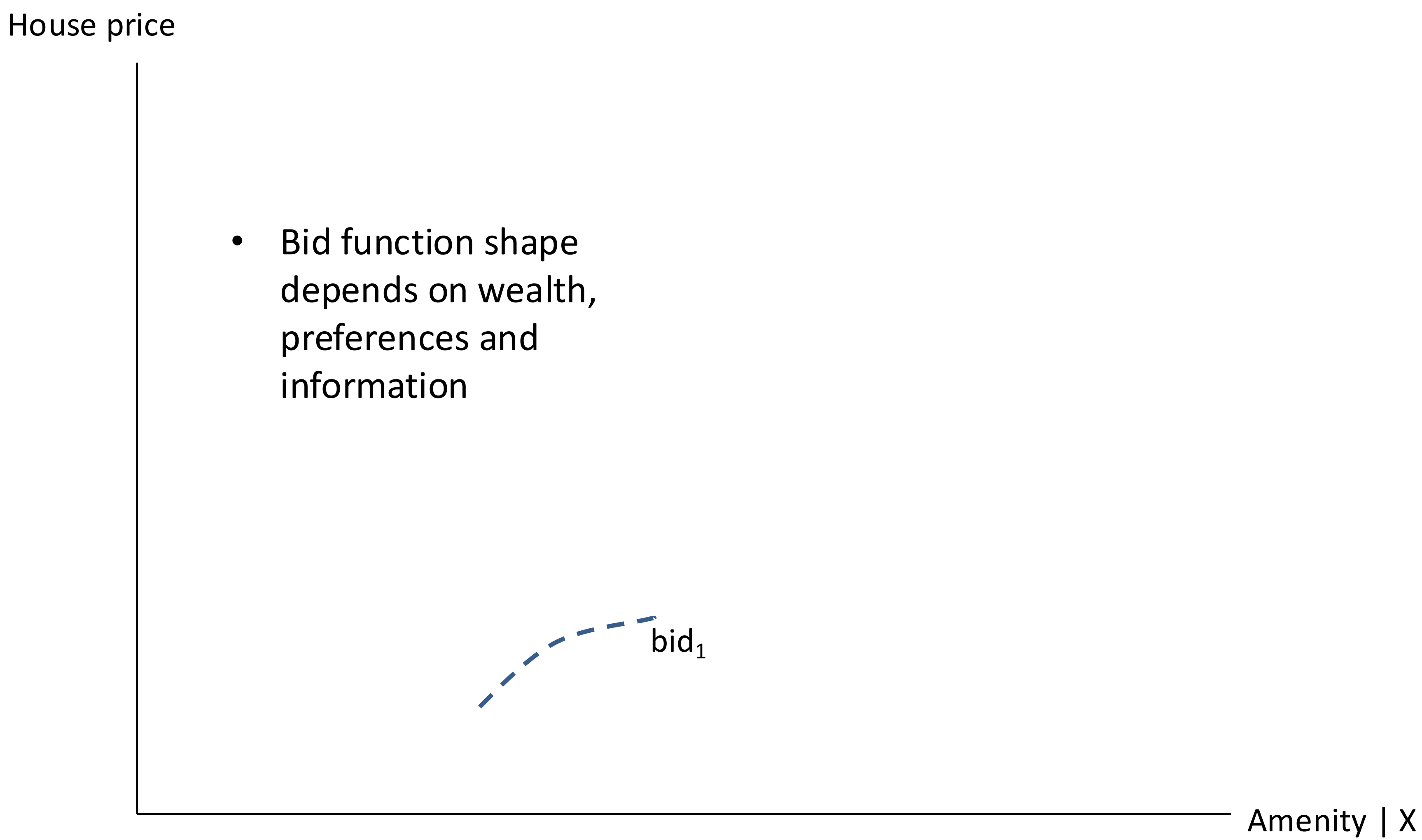
The Hedonic Property Value Model



The Hedonic Property Value Model

- Bid function shape depends on wealth, preferences and information



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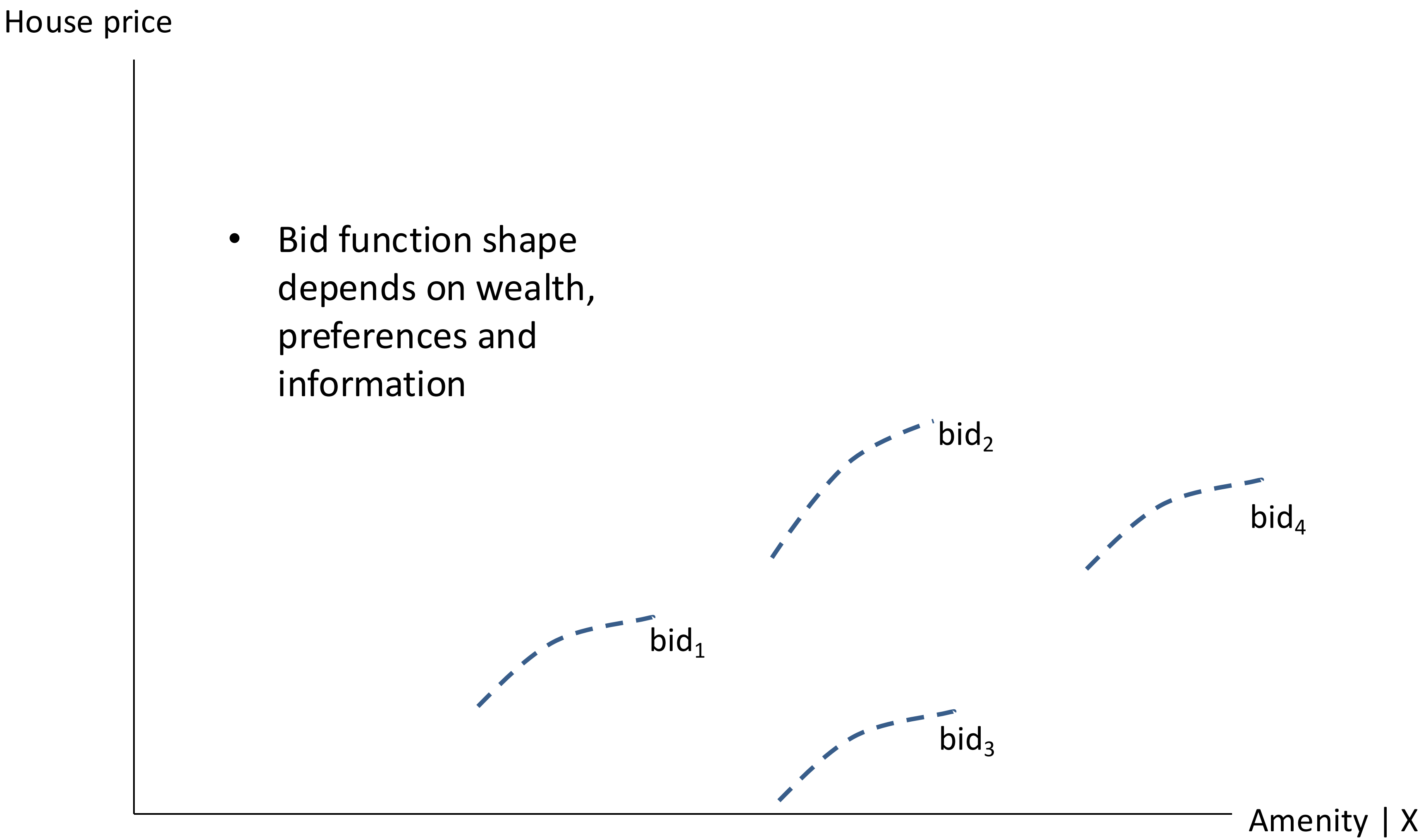

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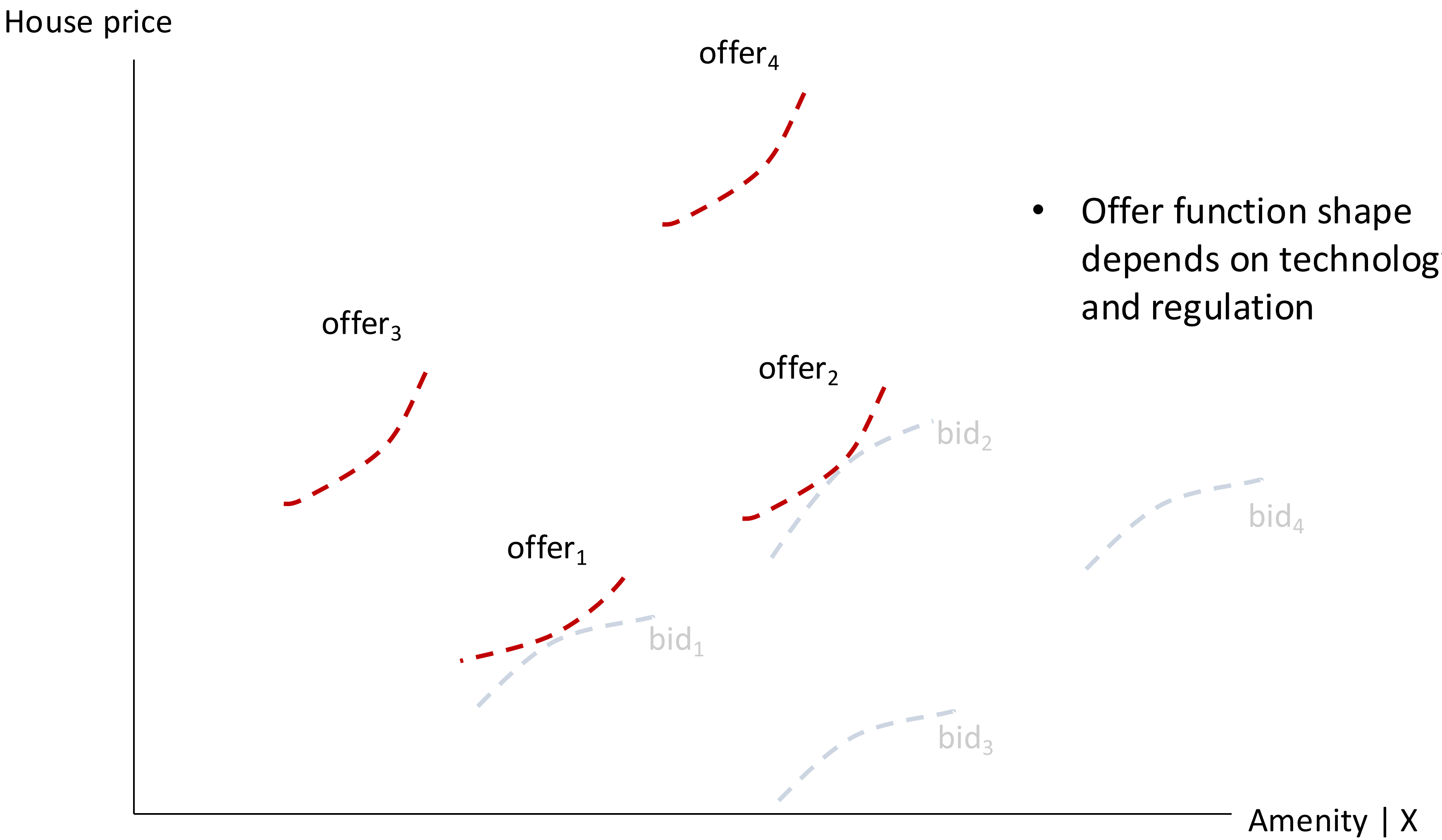
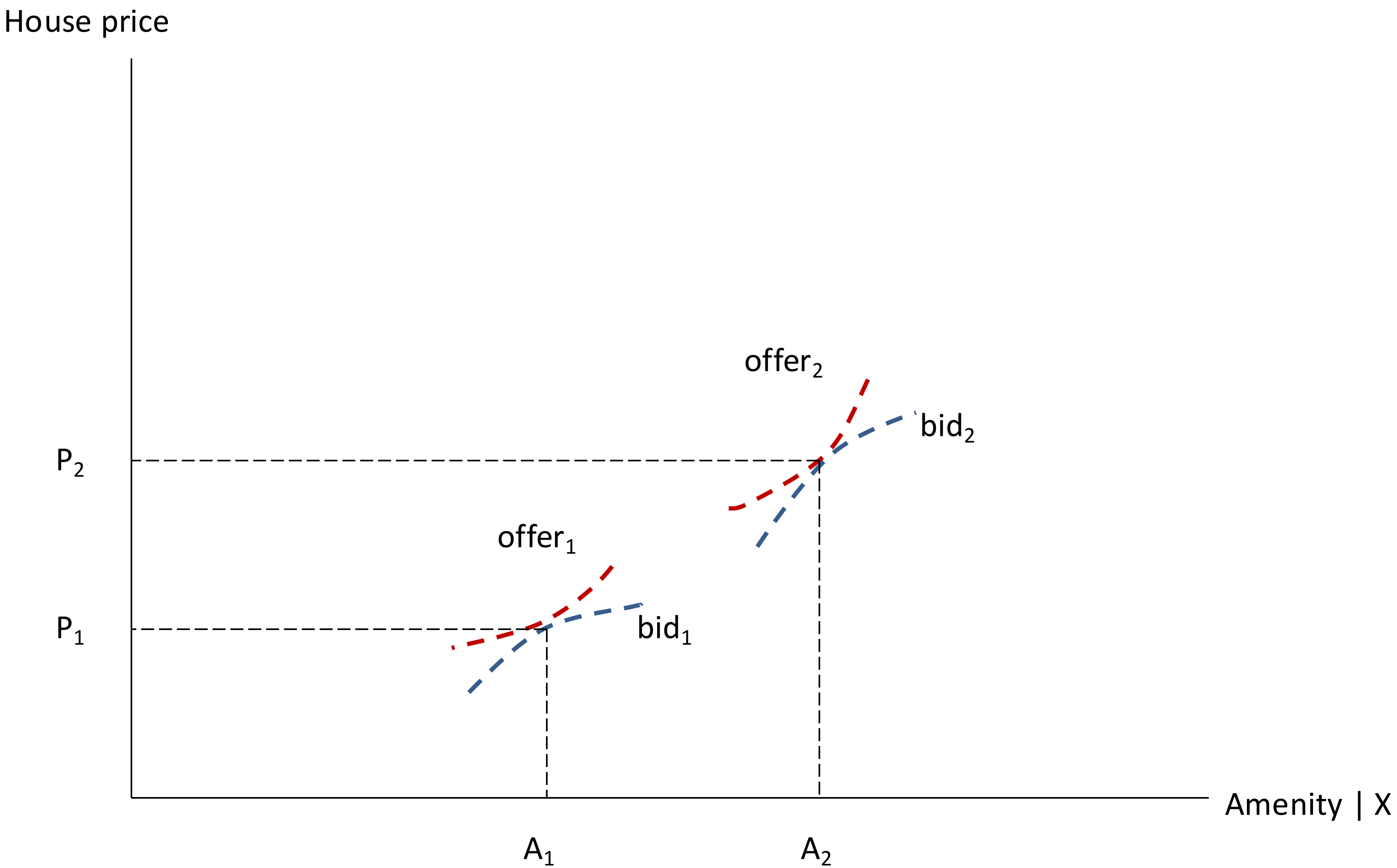


- Offer function shape depends on technology and regulation

The Hedonic Property Value Model



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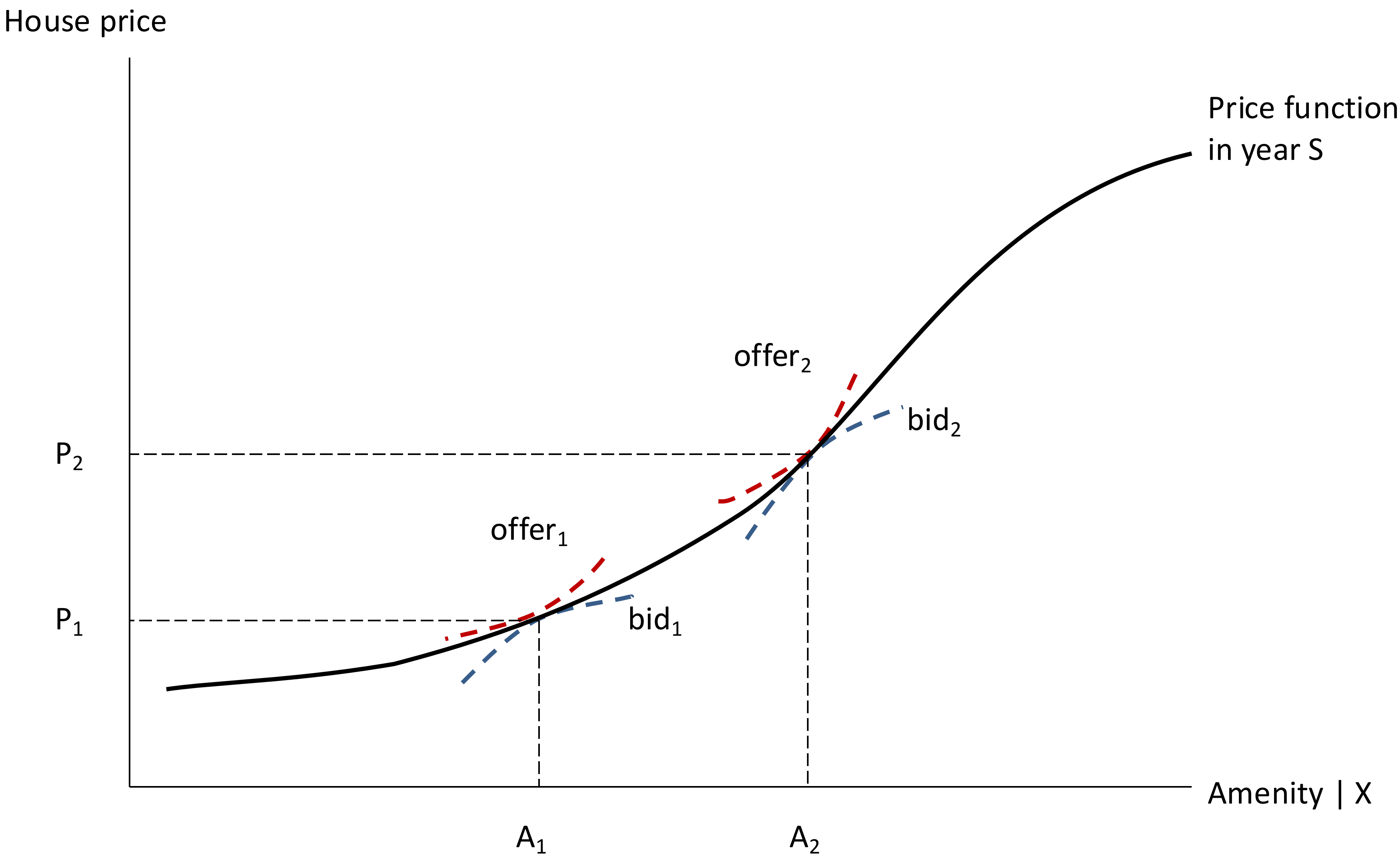

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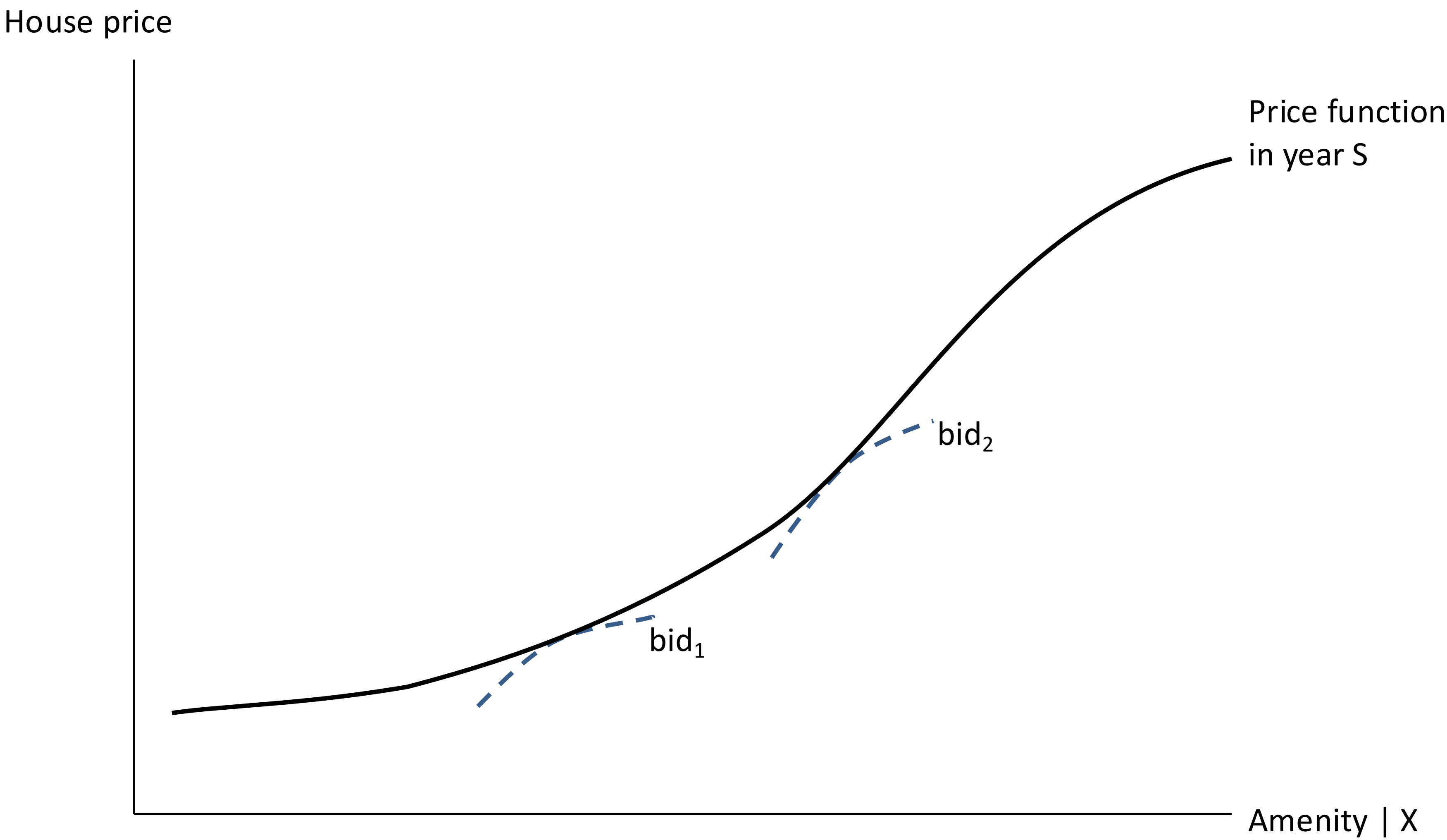
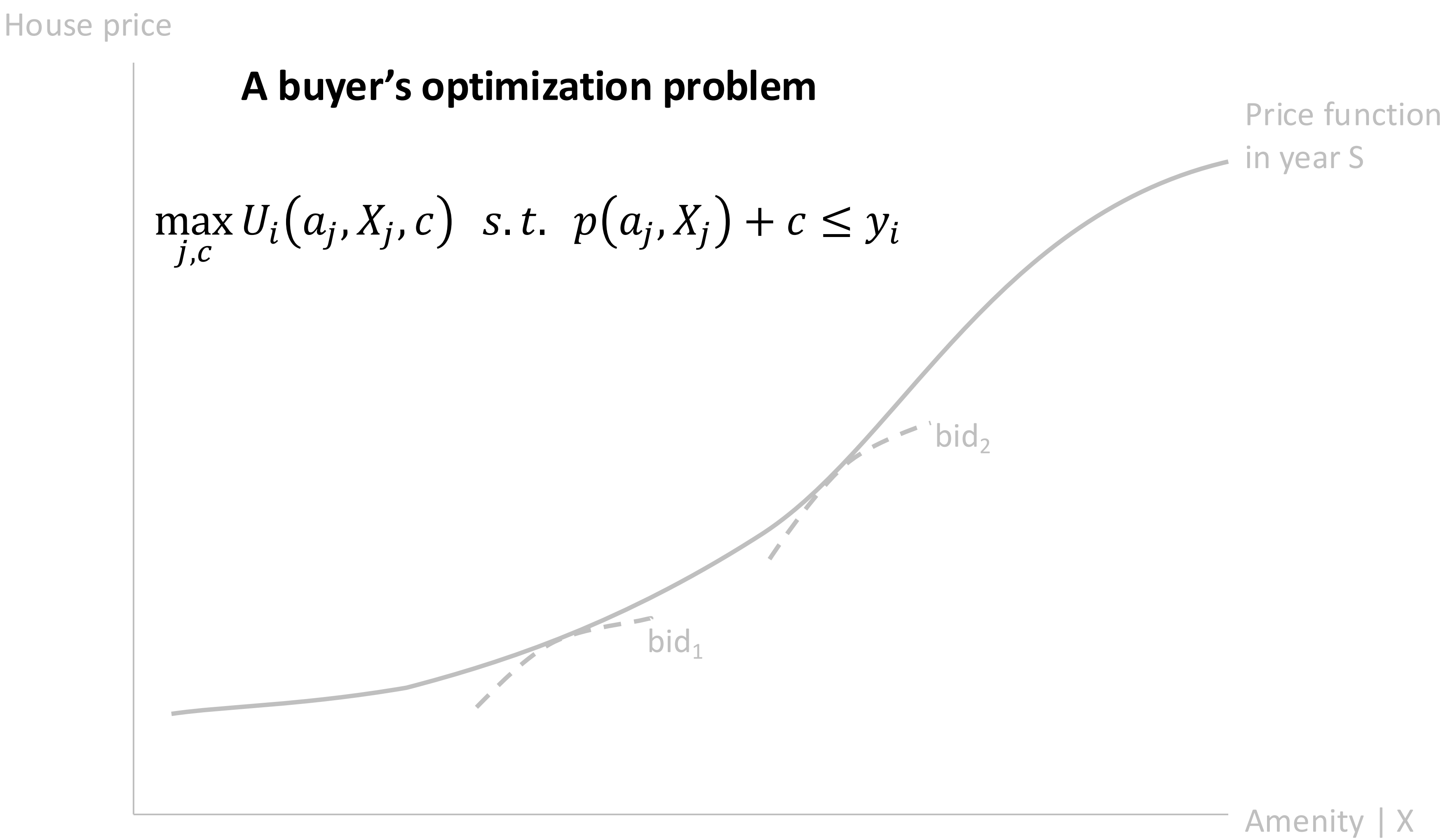


The Hedonic Property Value Model

A buyer's optimization problem

$$\max_{j,c} U_i\left(a_j, X_j, c\right) \;\; s.t. \;\; p\left(a_j, X_j\right) + c \leq y_i$$



The Hedonic Property Value Model

A buyer's optimization problem

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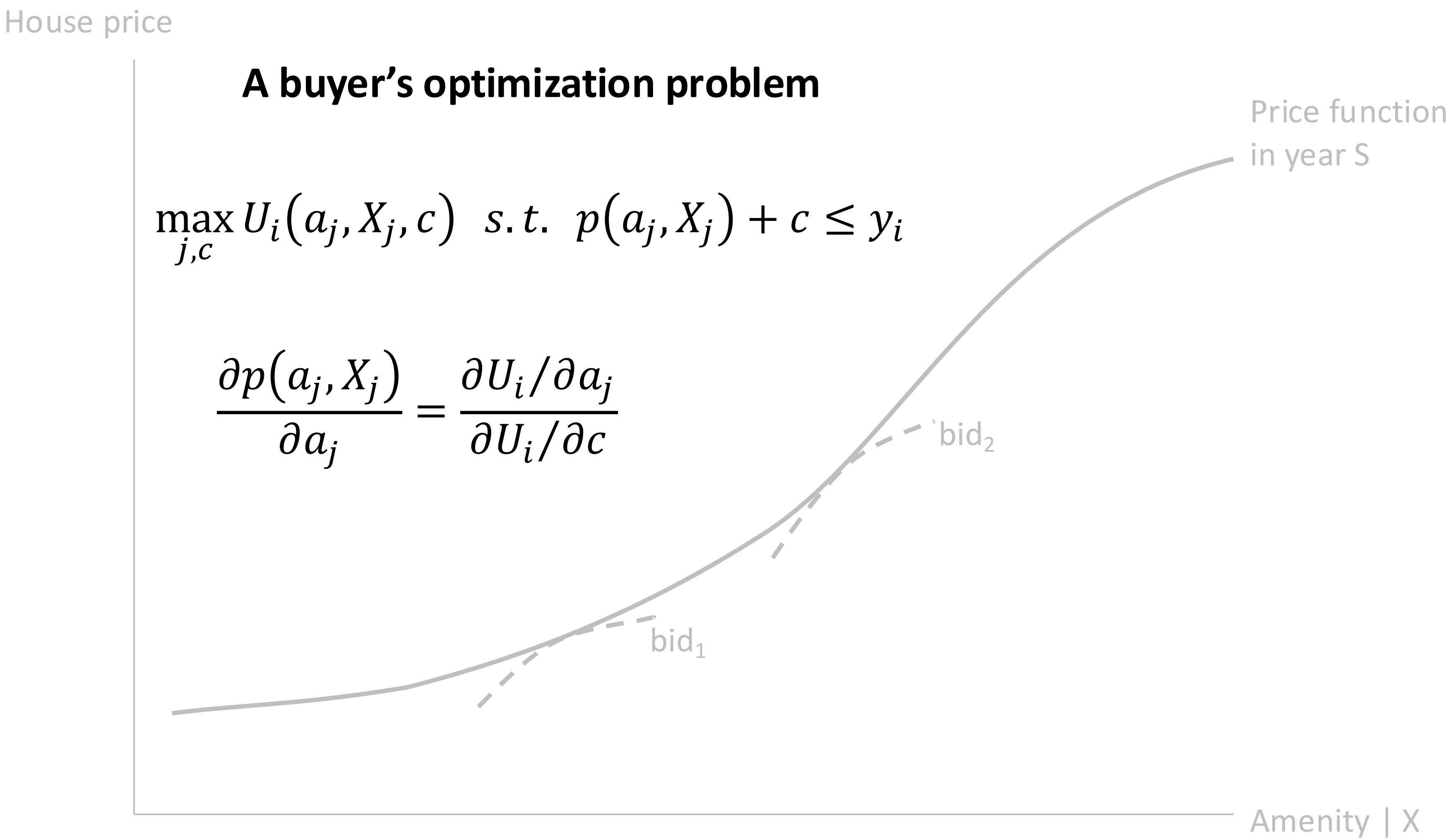
$$\frac{\partial p(a_j, X_j)}{\partial a_j} = \frac{\partial U_i / \partial a_j}{\partial U_i / \partial c}$$



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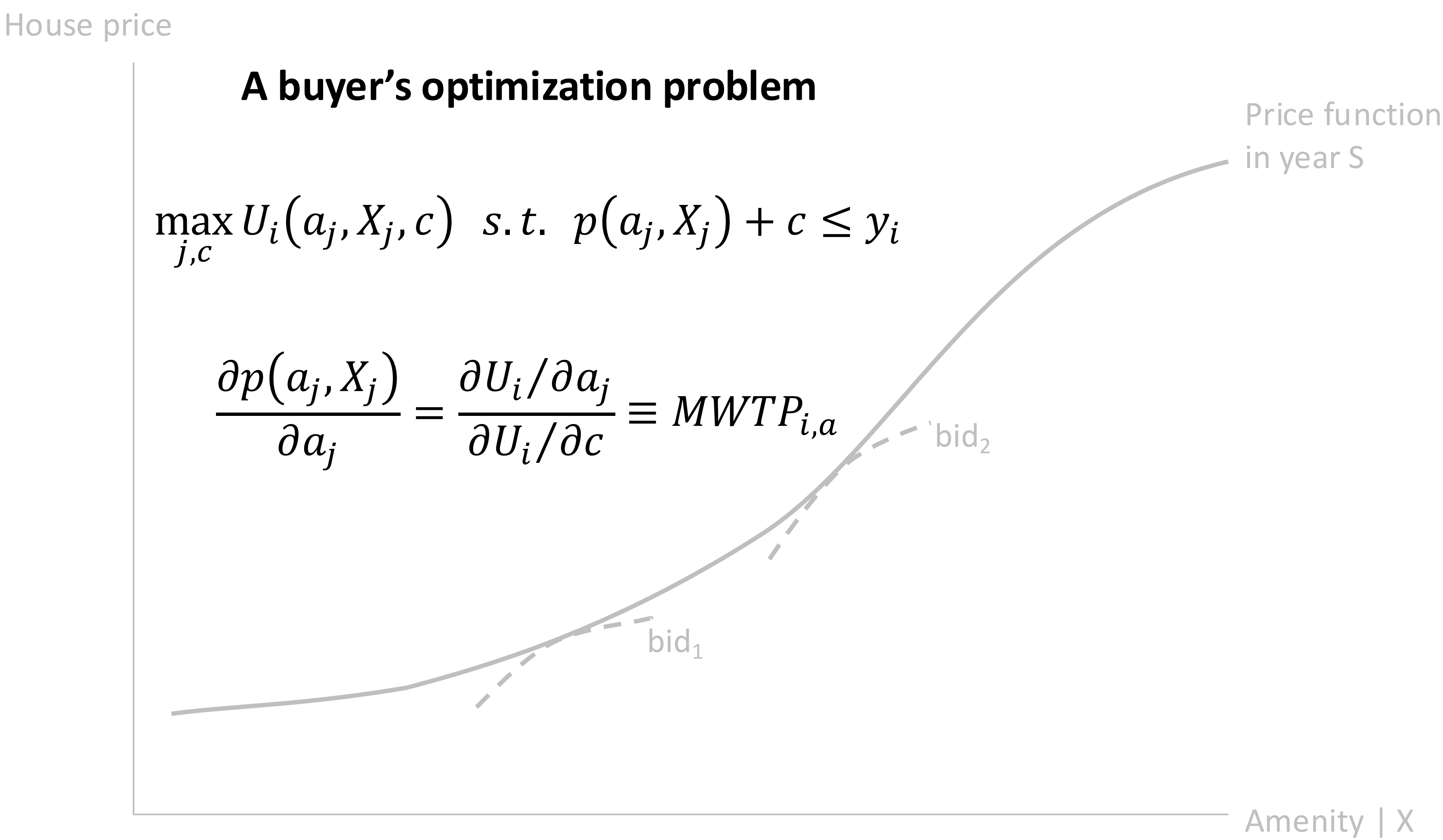
$$\frac{\partial p(a_j, X_j)}{\partial a_j} = \frac{\partial U_i / \partial a_j}{\partial U_i / \partial c} \equiv MWTP_{i,a}$$



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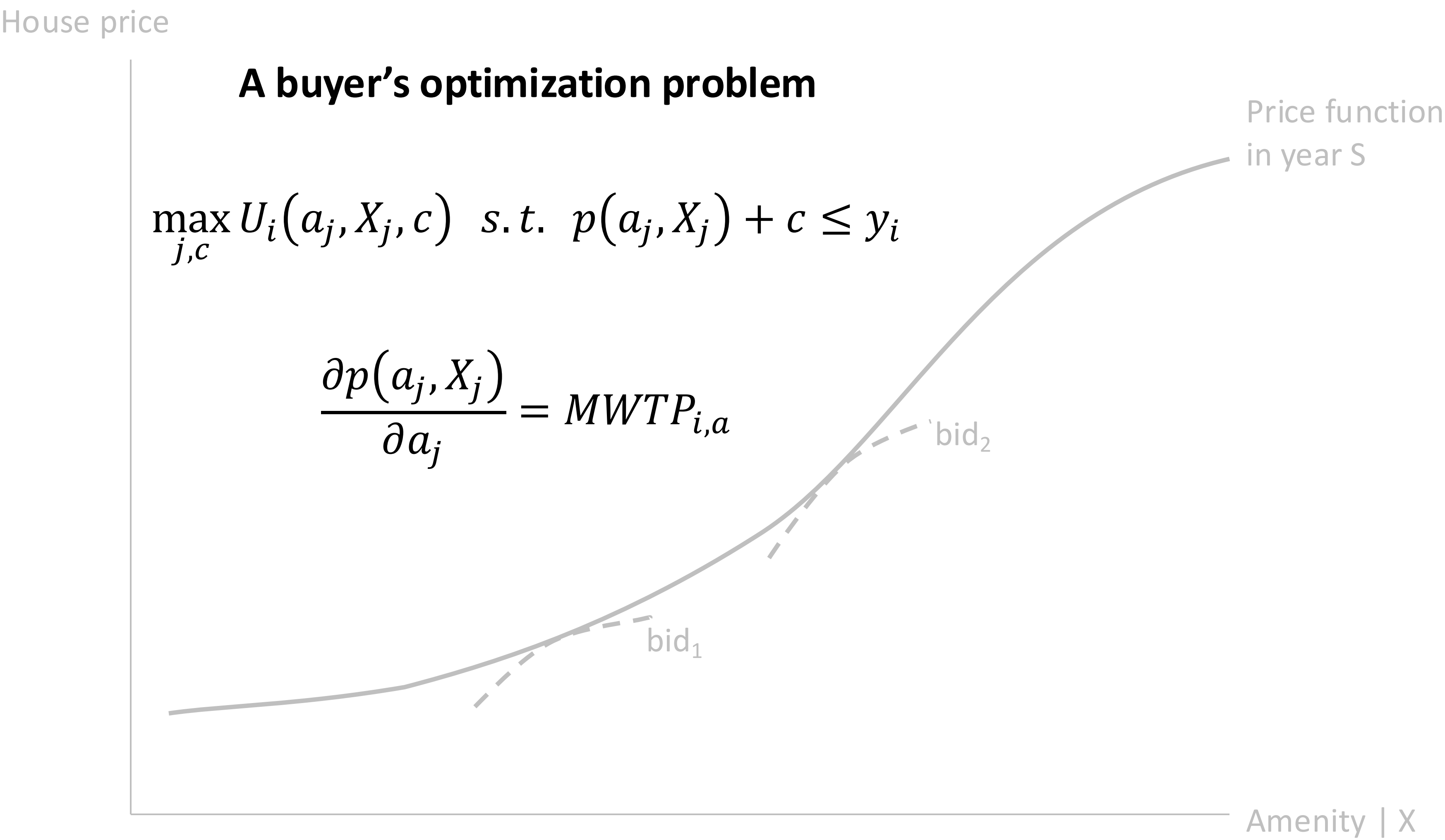


A buyer's optimization problem

$$\max_{j,c} U_i\left(a_j, X_j, c\right) \;\; s.t. \;\; p\left(a_j, X_j\right) + c \leq y_i$$

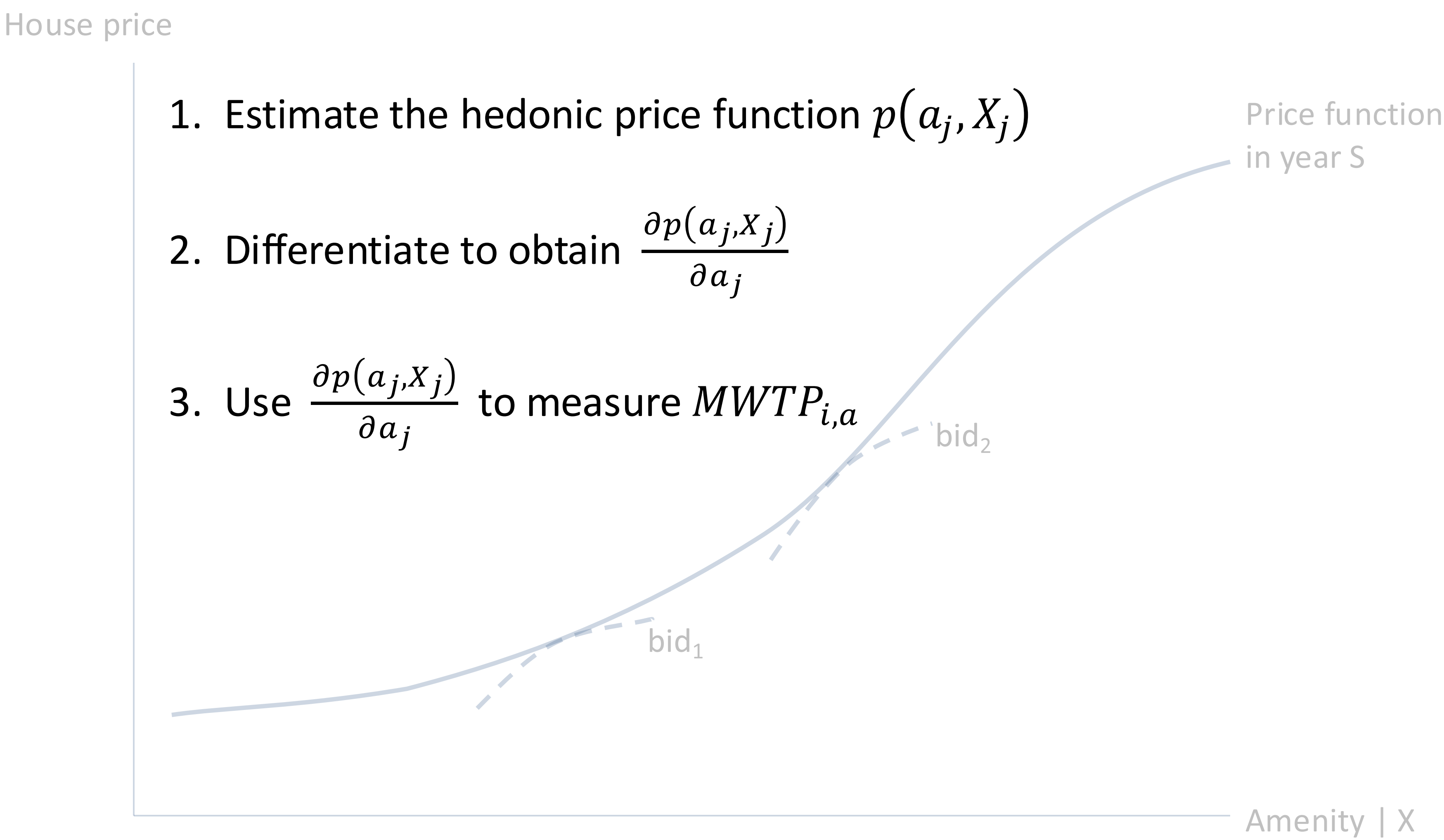
$$\frac{\partial p\left(a_j, X_j\right)}{\partial a_j} = MWTP_{i,a}$$

The Hedonic Property Value Model

1. Estimate the hedonic price function $p\left(a_j, X_j\right)$

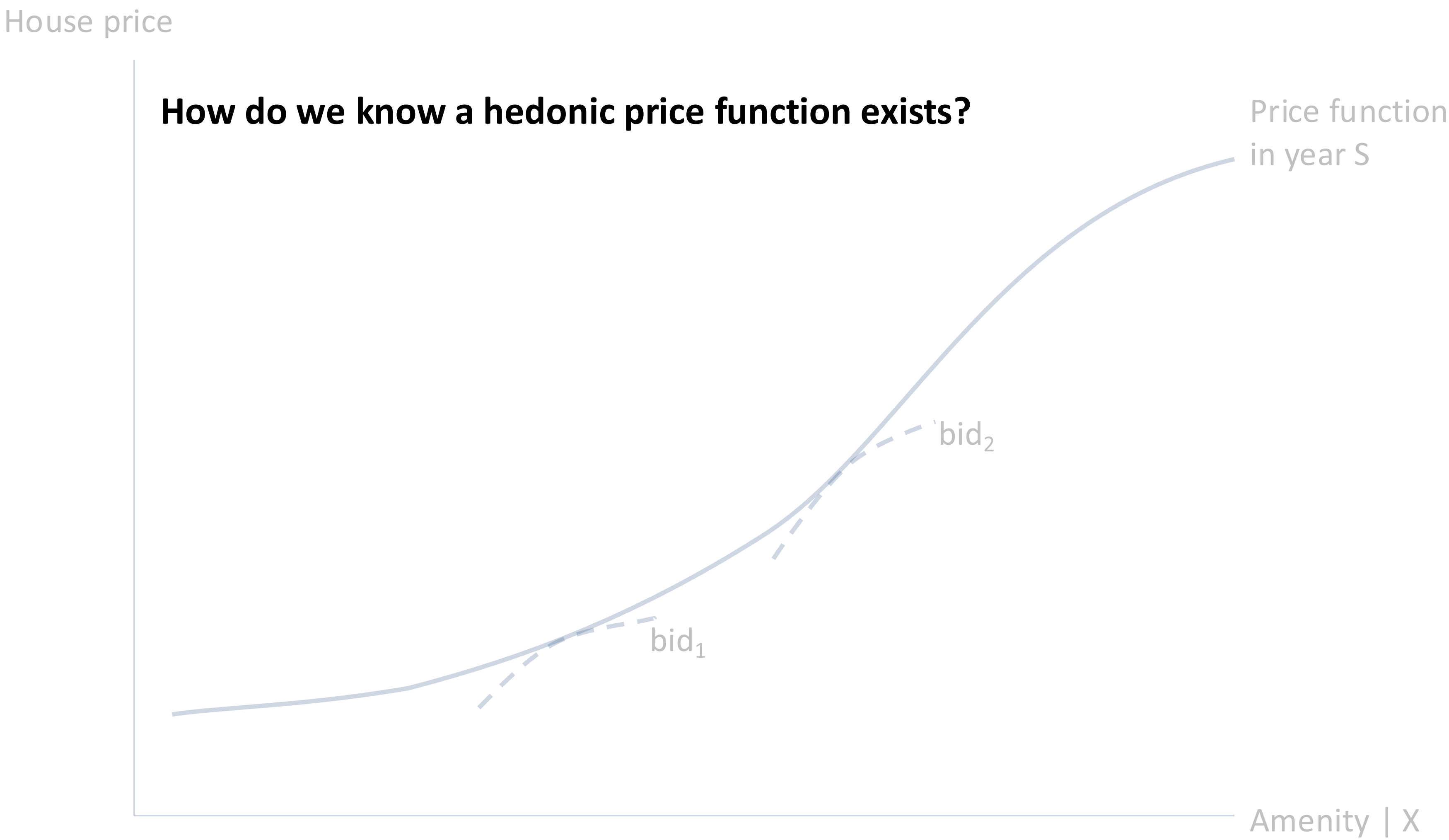
2. Differentiate to obtain $\frac{\partial p(a_j, X_j)}{\partial a_j}$

3. Use $\frac{\partial p(a_j, X_j)}{\partial a_j}$ to measure $MWTP_{i,a}$



The Hedonic Property Value Model

How do we know a hedonic price function exists?



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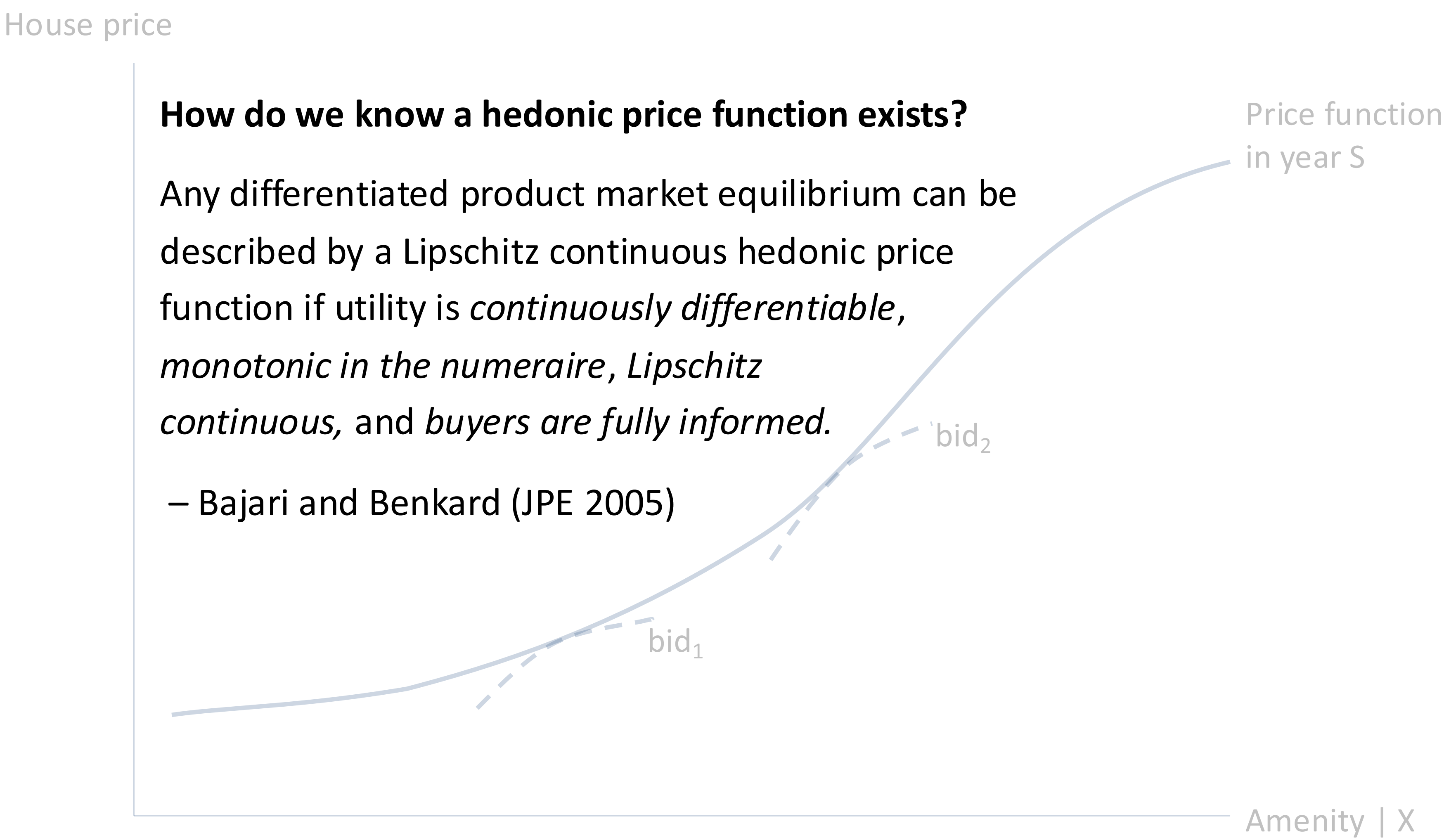


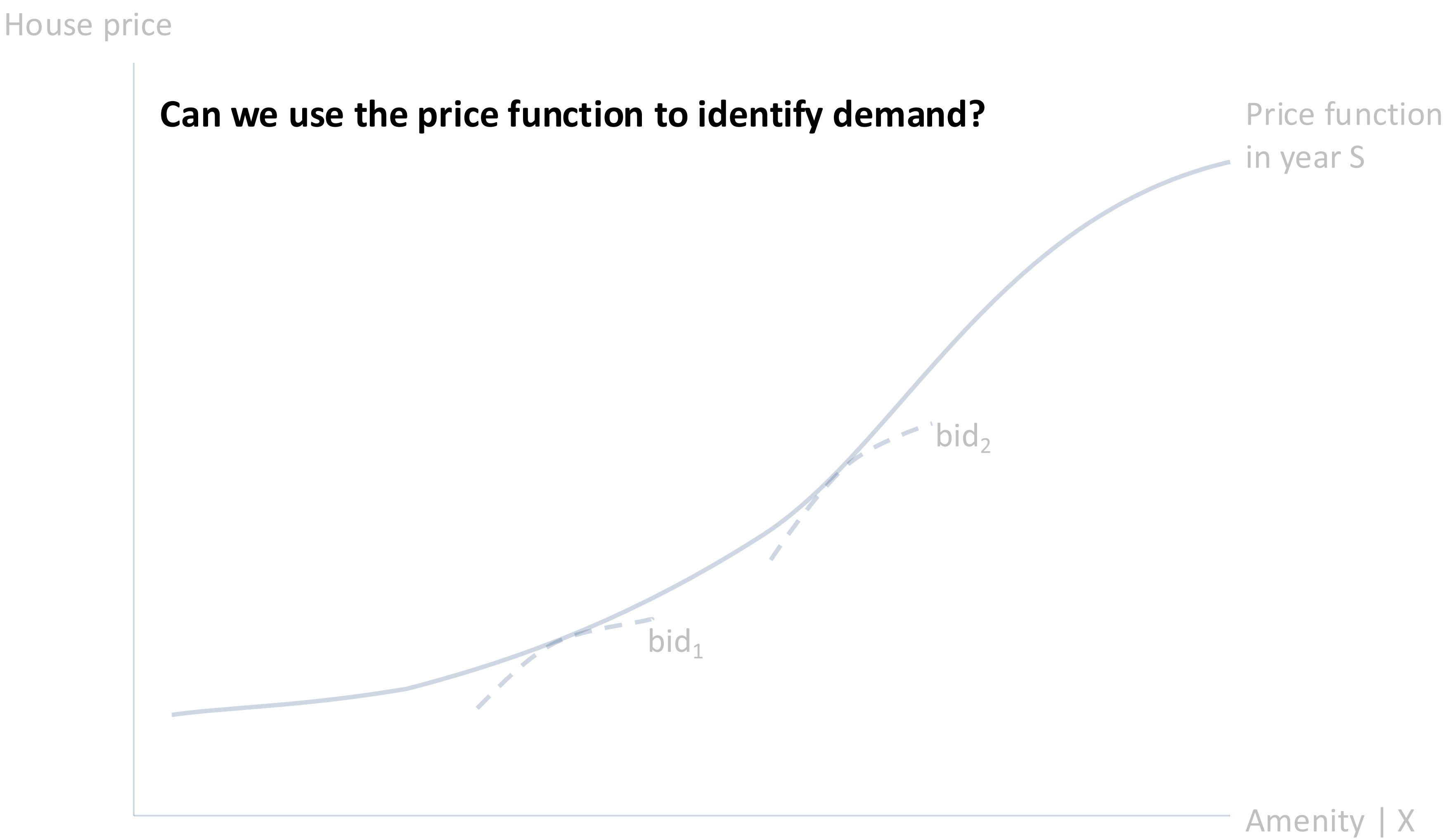
How do we know a hedonic price function exists?

Any differentiated product market equilibrium can be described by a Lipschitz continuous hedonic price function if utility is *continuously differentiable*, *monotonic in the numeraire*, *Lipschitz continuous,* and *buyers are fully informed.*

– Bajari and Benkard (JPE 2005)

The Hedonic Property Value Model

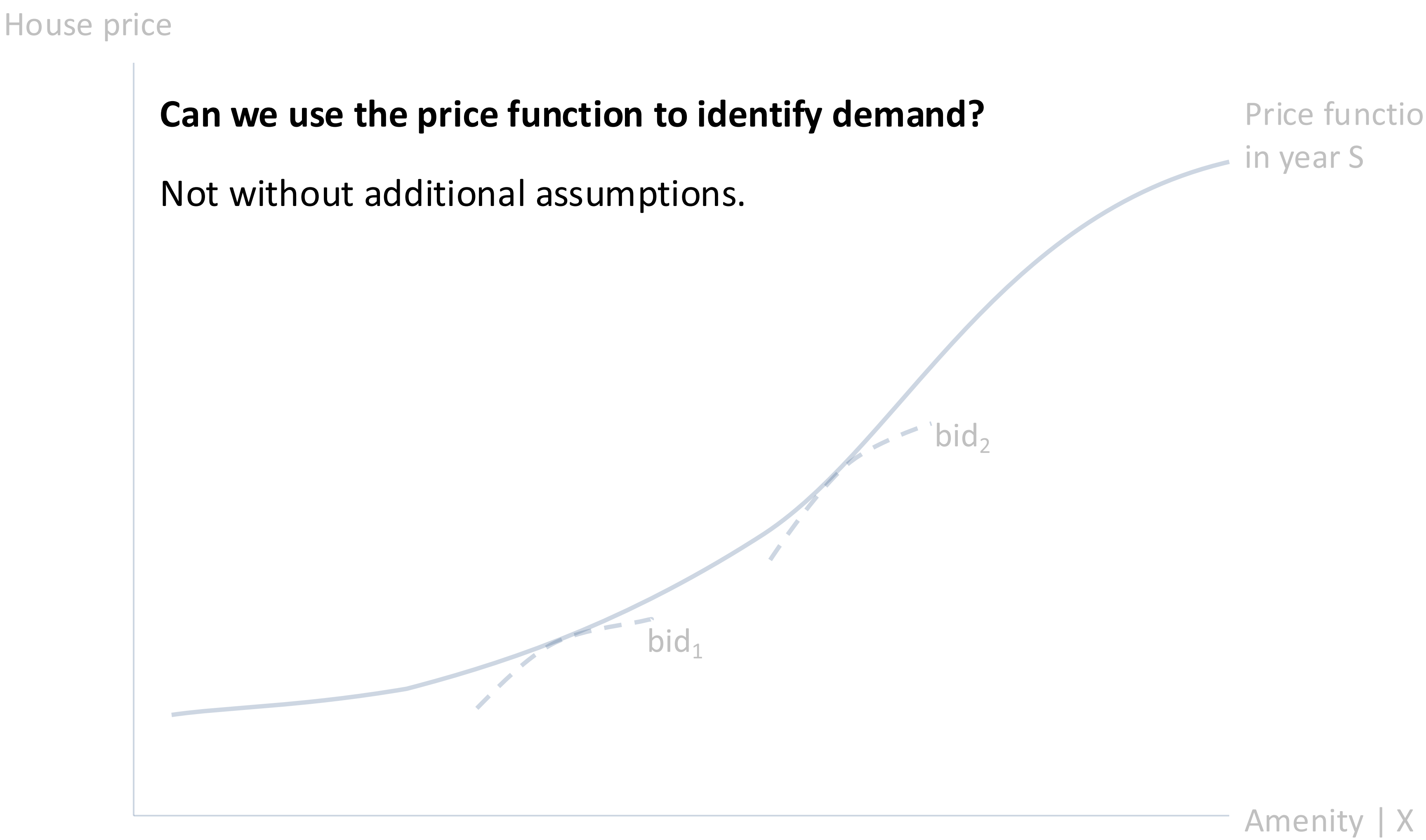
Can we use the price function to identify demand?



The Hedonic Property Value Model

Can we use the price function to identify demand?

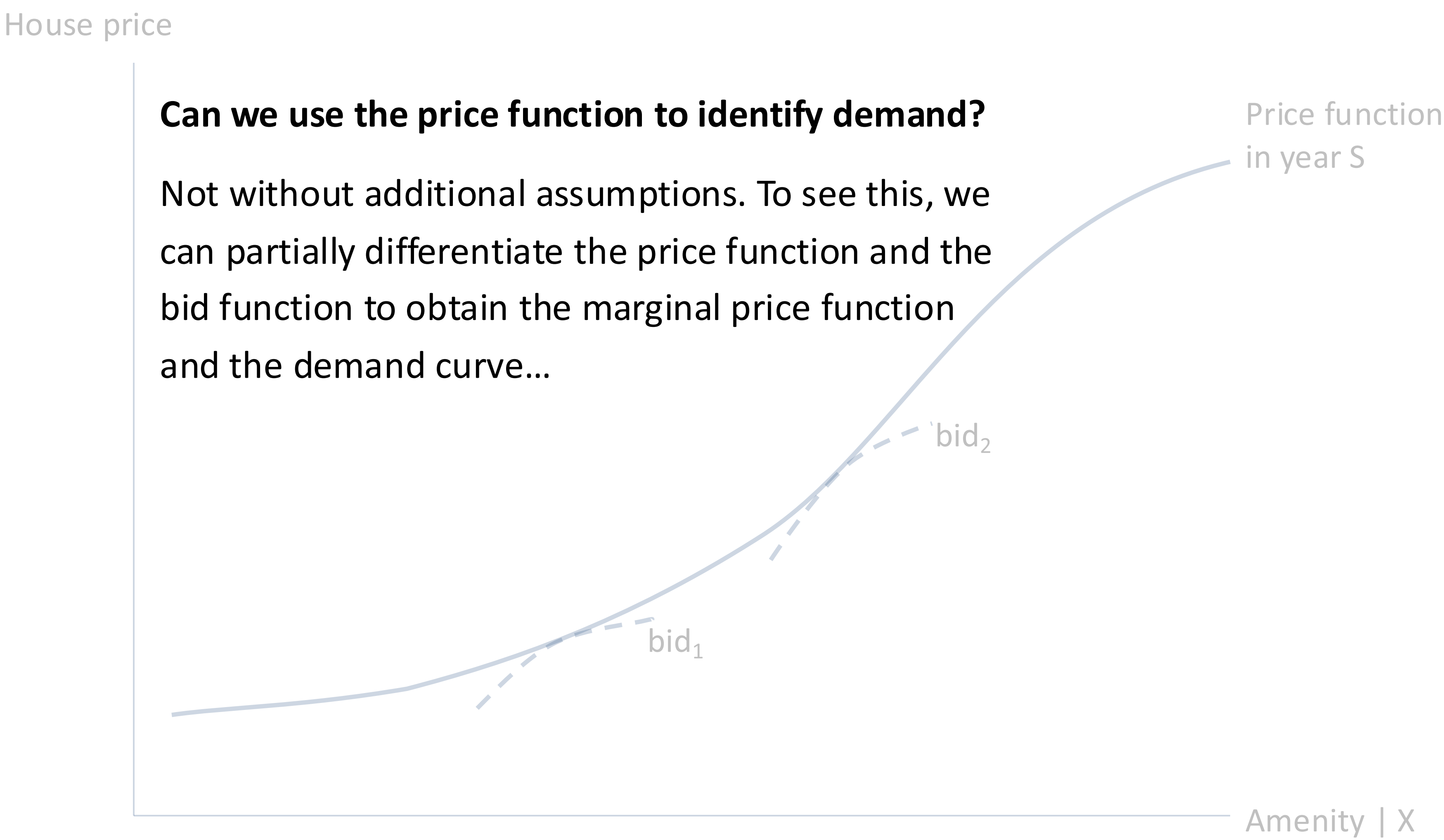
Not without additional assumptions.



The Hedonic Property Value Model

Can we use the price function to identify demand?

Not without additional assumptions. To see this, we can partially differentiate the price function and the bid function to obtain the marginal price function and the demand curve…



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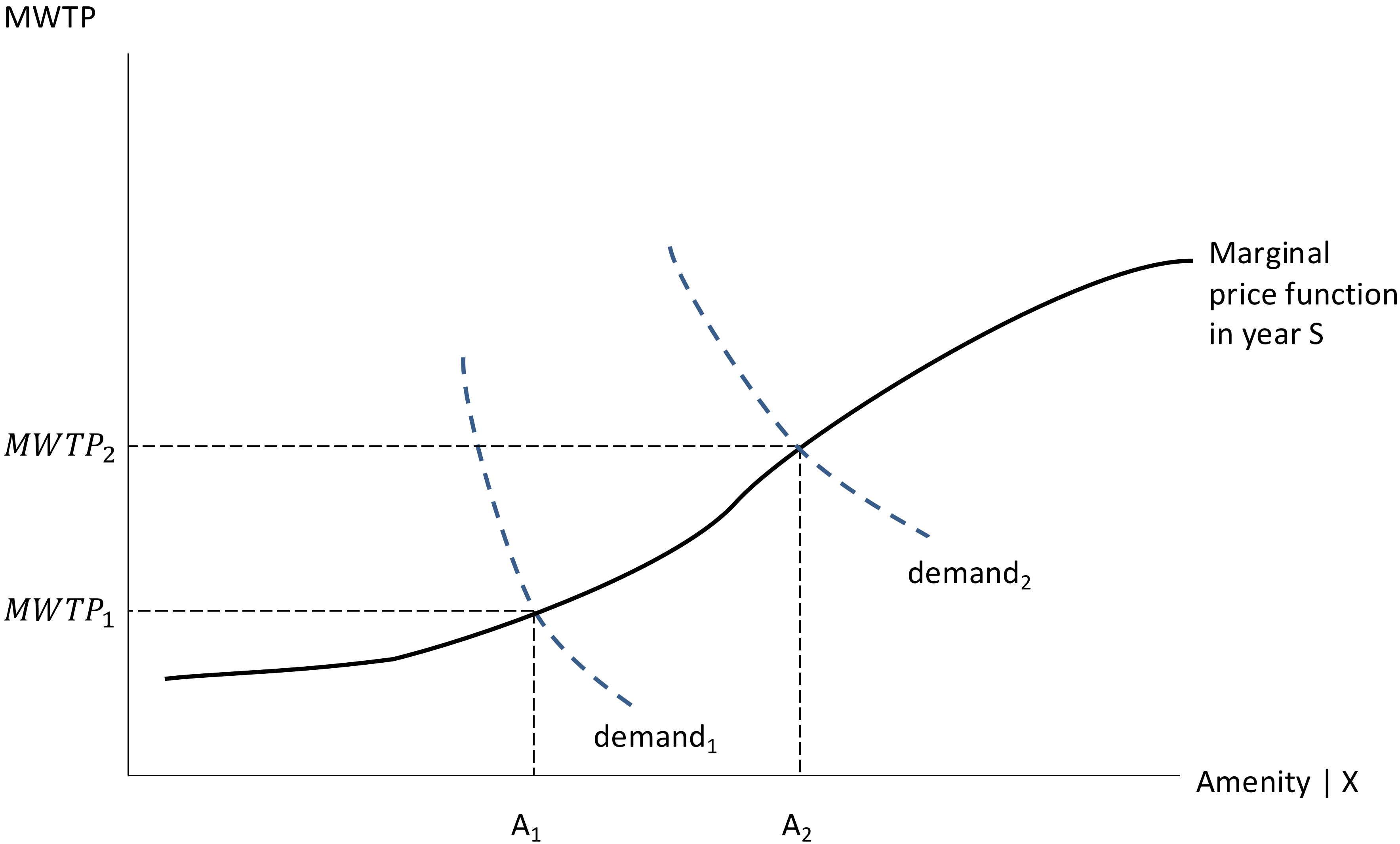

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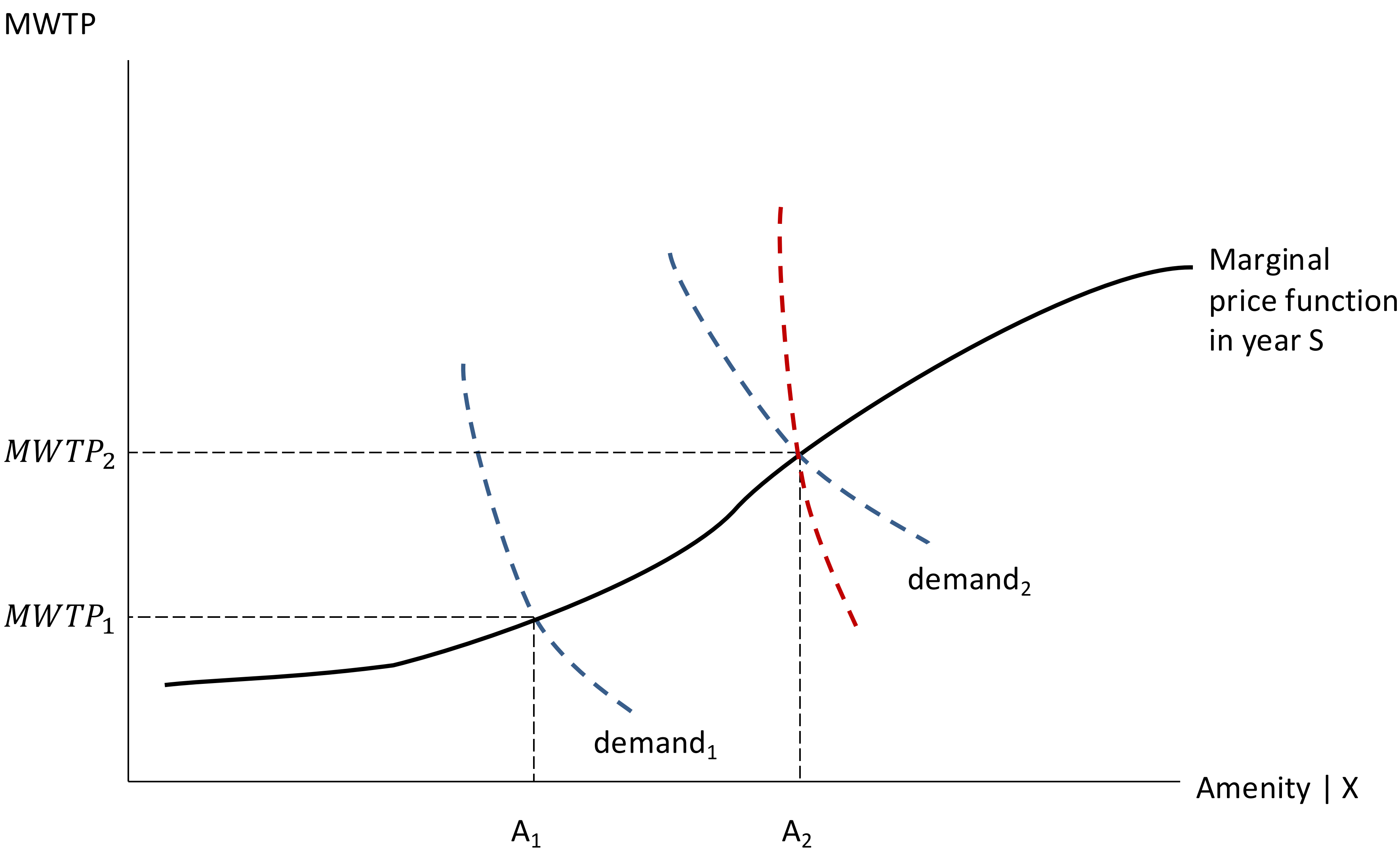

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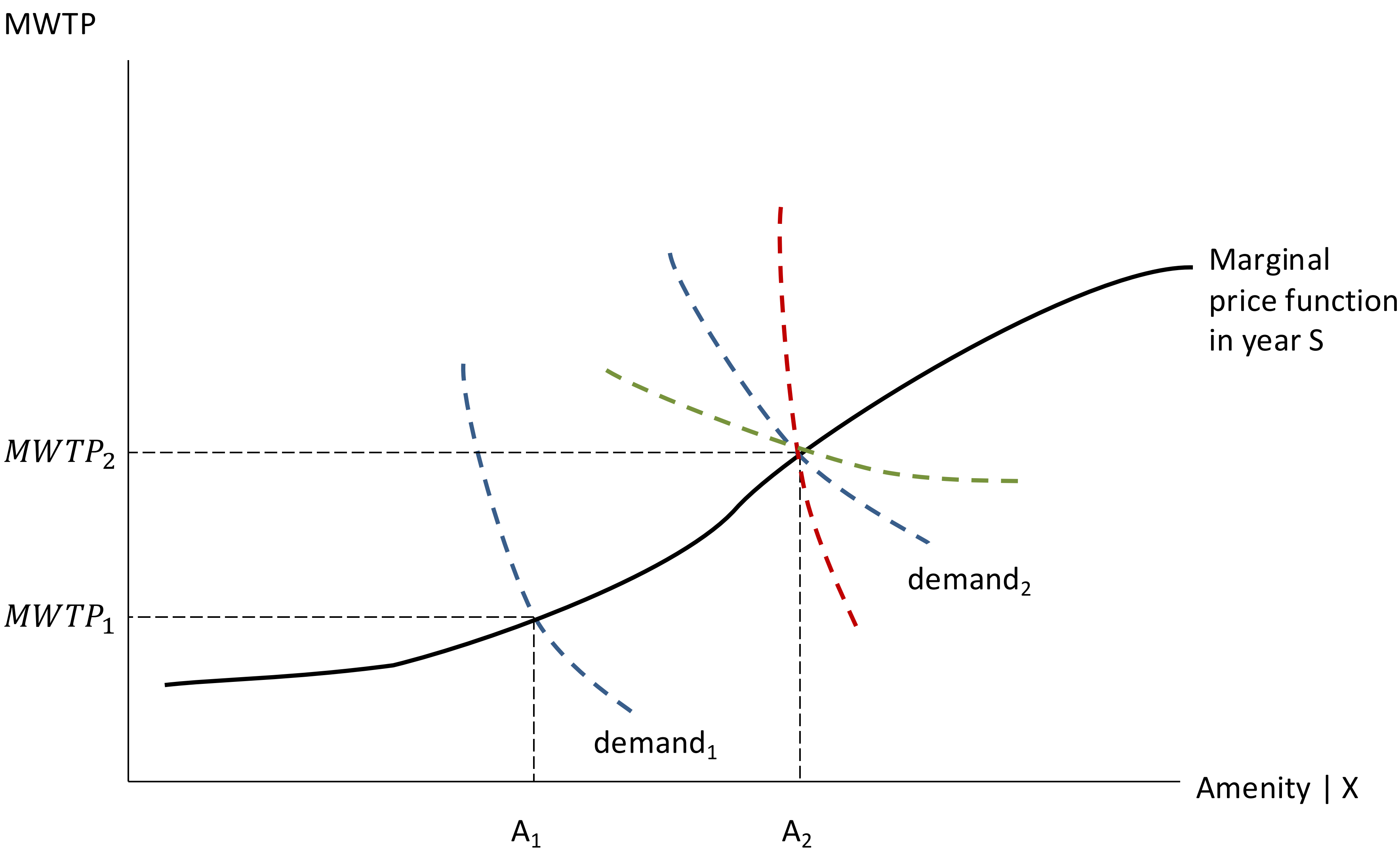
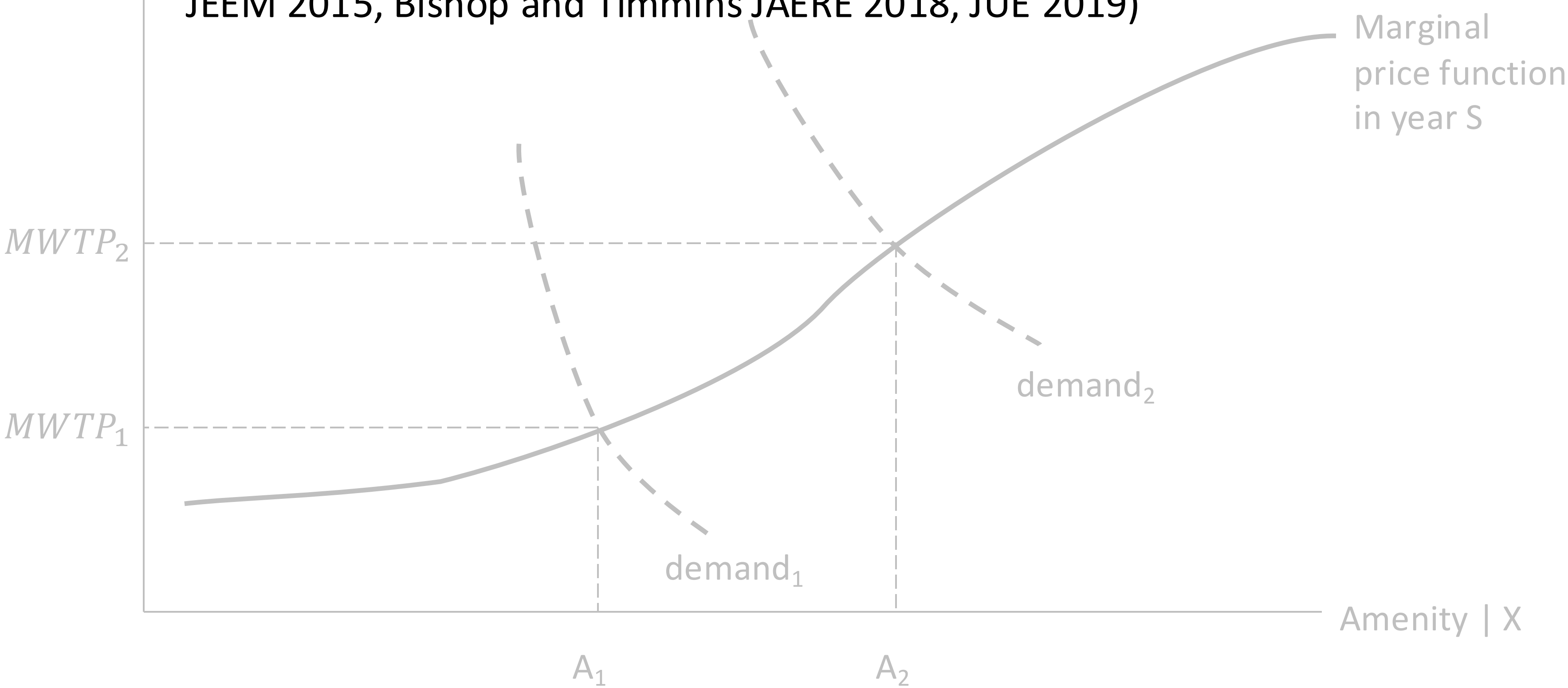


The Hedonic Property Value Model

Identifying demand requires additional restrictions (e.g. on preferences).
(e.g. Epple JPE 1987, Ekeland, Heckman, Nesheim JPE 2004, Bajari and Benkard JPE 2005, Kuminoff and Pope EL 2012, Zhang, Boyle and Kuminoff JEEM 2015, Bishop and Timmins JAERE 2018, JUE 2019)



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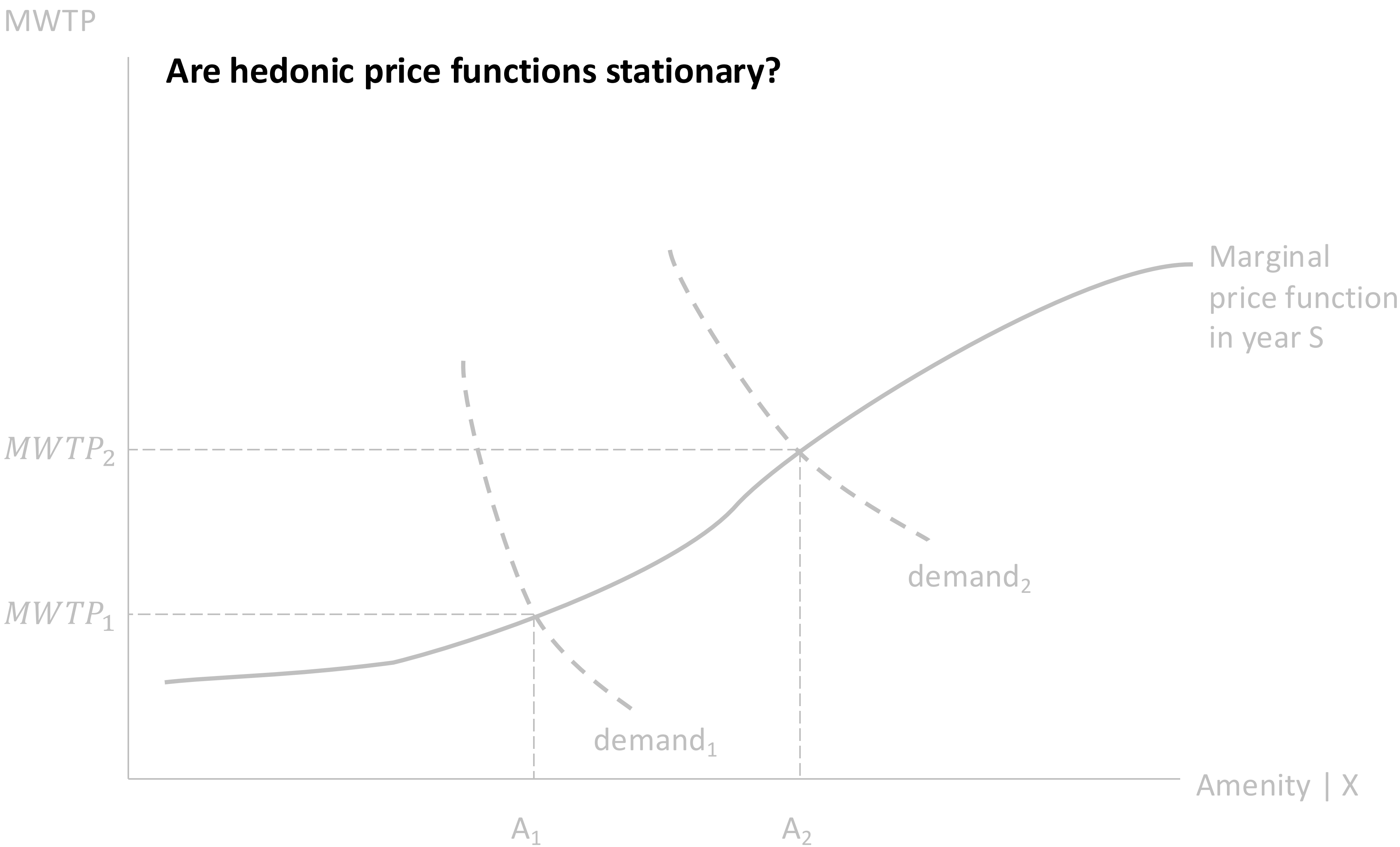
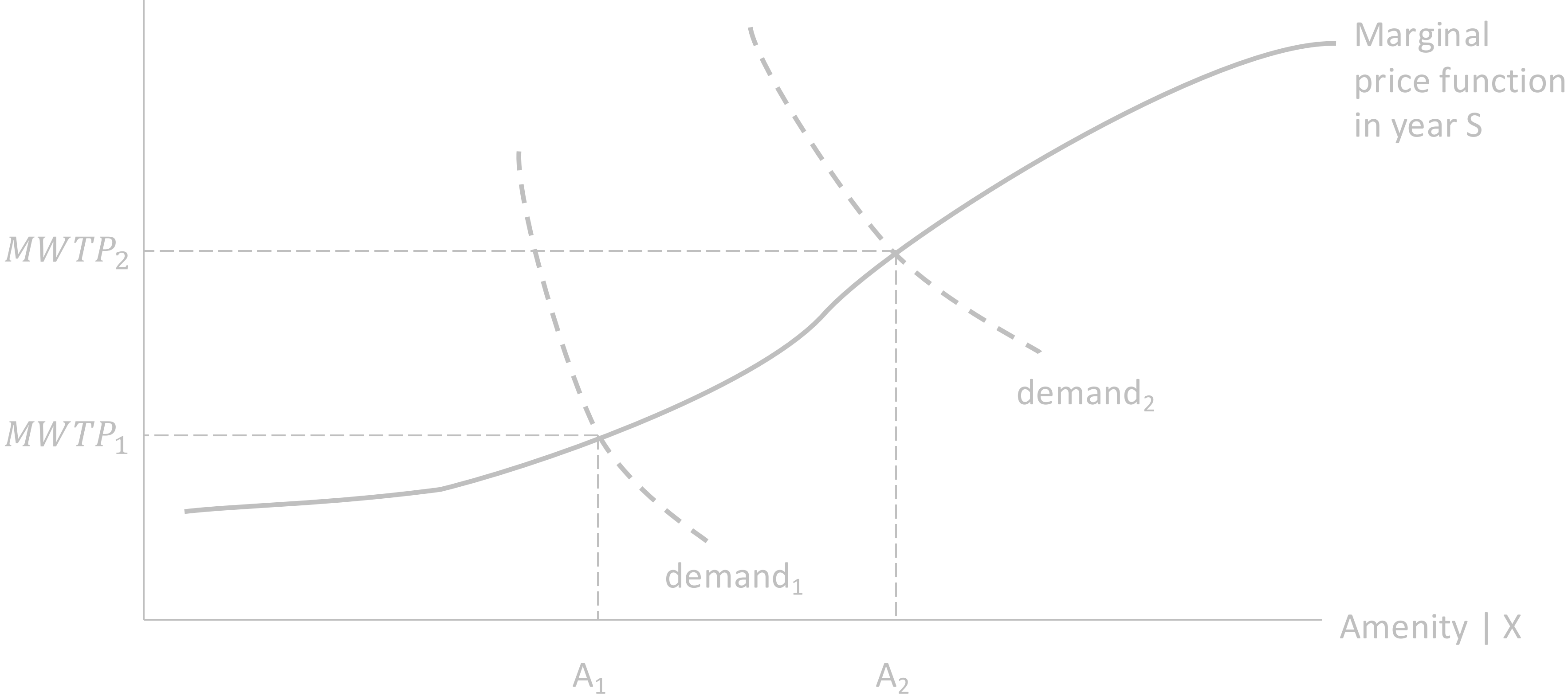


The Hedonic Property Value Model

Are hedonic price functions stationary?

Not without additional assumptions (Kuminoff and Pope IER 2014, Banzhaf IER 2020, JPE 2021)



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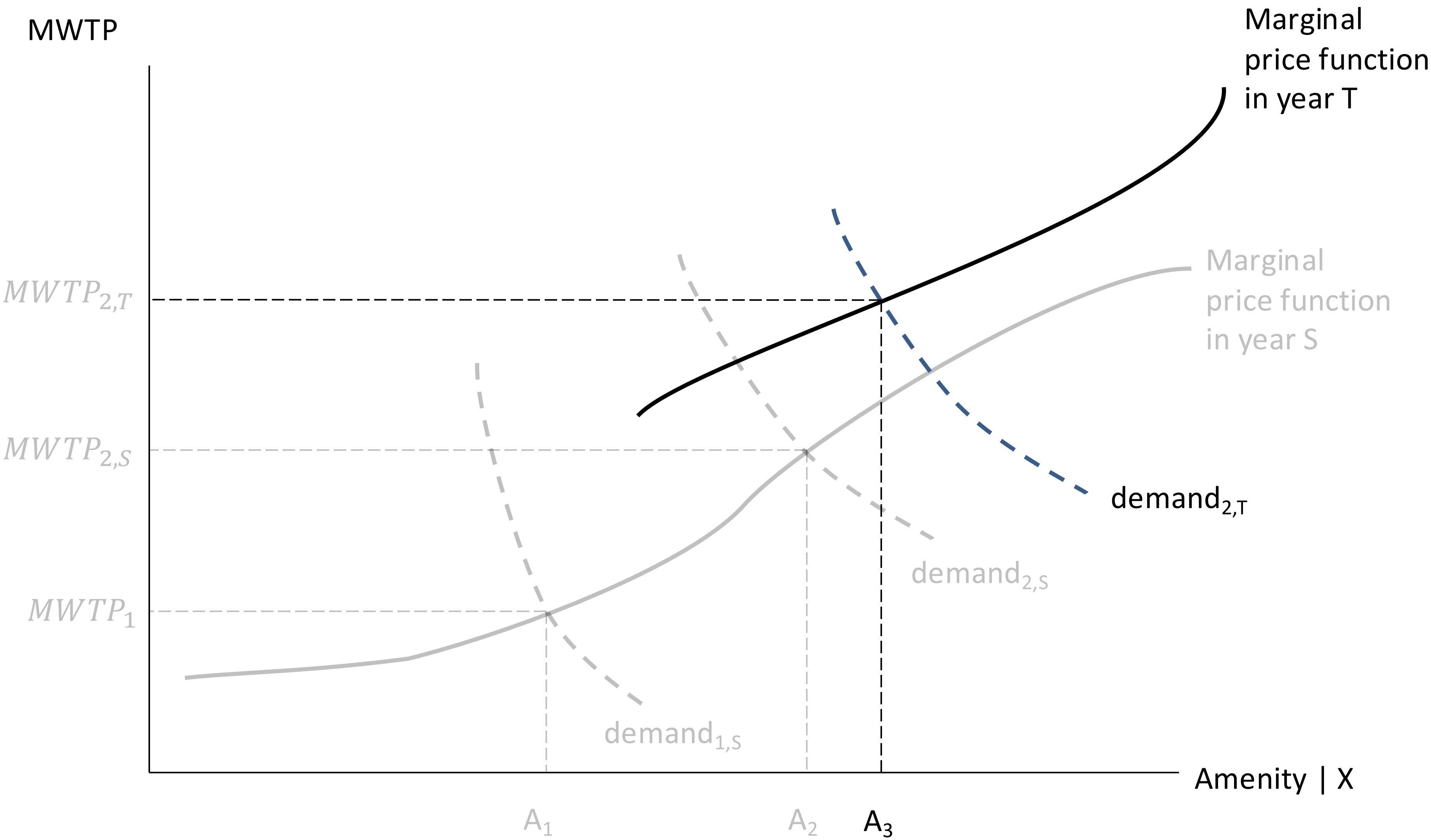

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Estimating MWTP: Market Definition

Best practice – geographic area in which buyers can make ceteris paribus moves during an interval when the "*law of one price function*" holds (e.g. a single metropolitan area in a single year)

Issues with alternative market definitions

- Larger areas may embed other constraints and margins of adjustment (e.g. moving cost, wages, taxes, cost-of-living)

- Longer time periods may embed changes in the the price function (e.g. boom-bust cycles, regulation, information)

Can pool data and allow for spatiotemporal variation in price functions

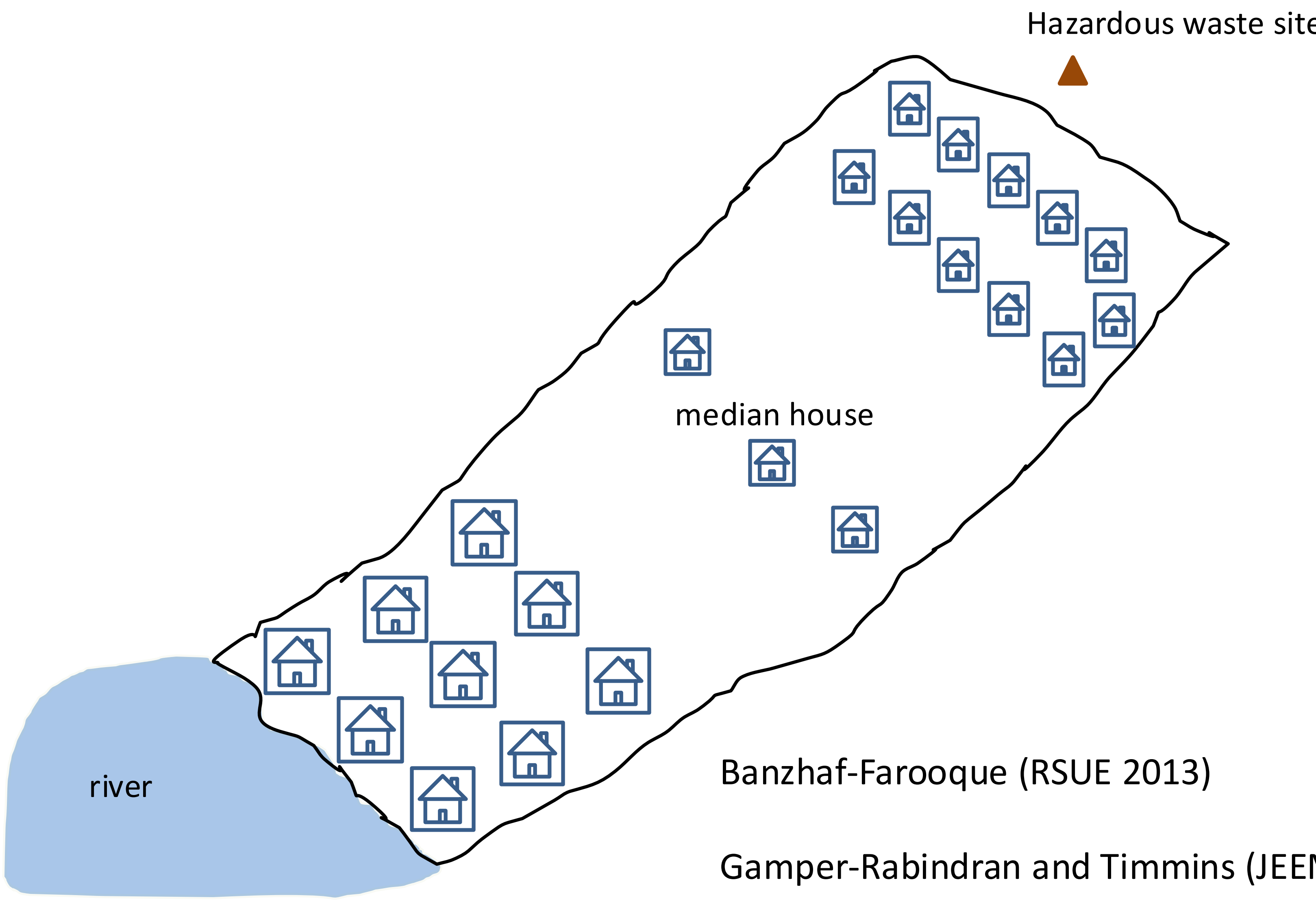
Estimating MWTP: Data Collection

Best practice – random sample of micro data on arm's length property transactions, describing sale prices and physical characteristics

Issues with other common data formats

- Predicted values may introduce non-random measurement error (e.g. Census self-reports, appraisals)
- Spatially aggregated data (e.g. means or medians) do not have a known mapping to a hedonic price function

Example: Median House is Unaffected by Amenities

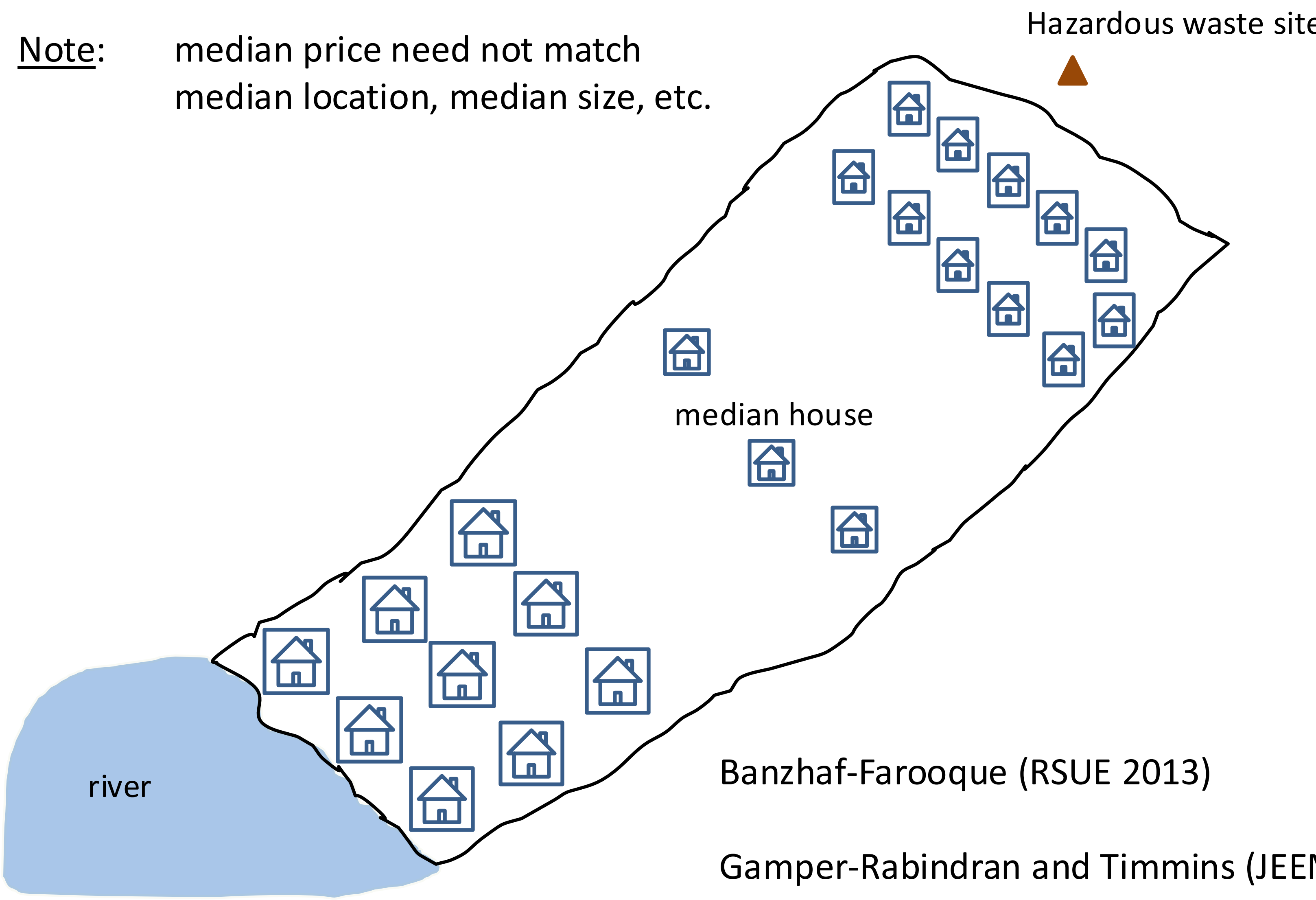


Banzhaf-Farooque (RSUE 2013)

Gamper-Rabindran and Timmins (JEEM 2013)

Example: Median House is Unaffected by Amenities

<u>Note</u>: median price need not match median location, median size, etc.



Banzhaf-Farooque (RSUE 2013)

Gamper-Rabindran and Timmins (JEEM 2013)

Estimating MWTP: Data Collection

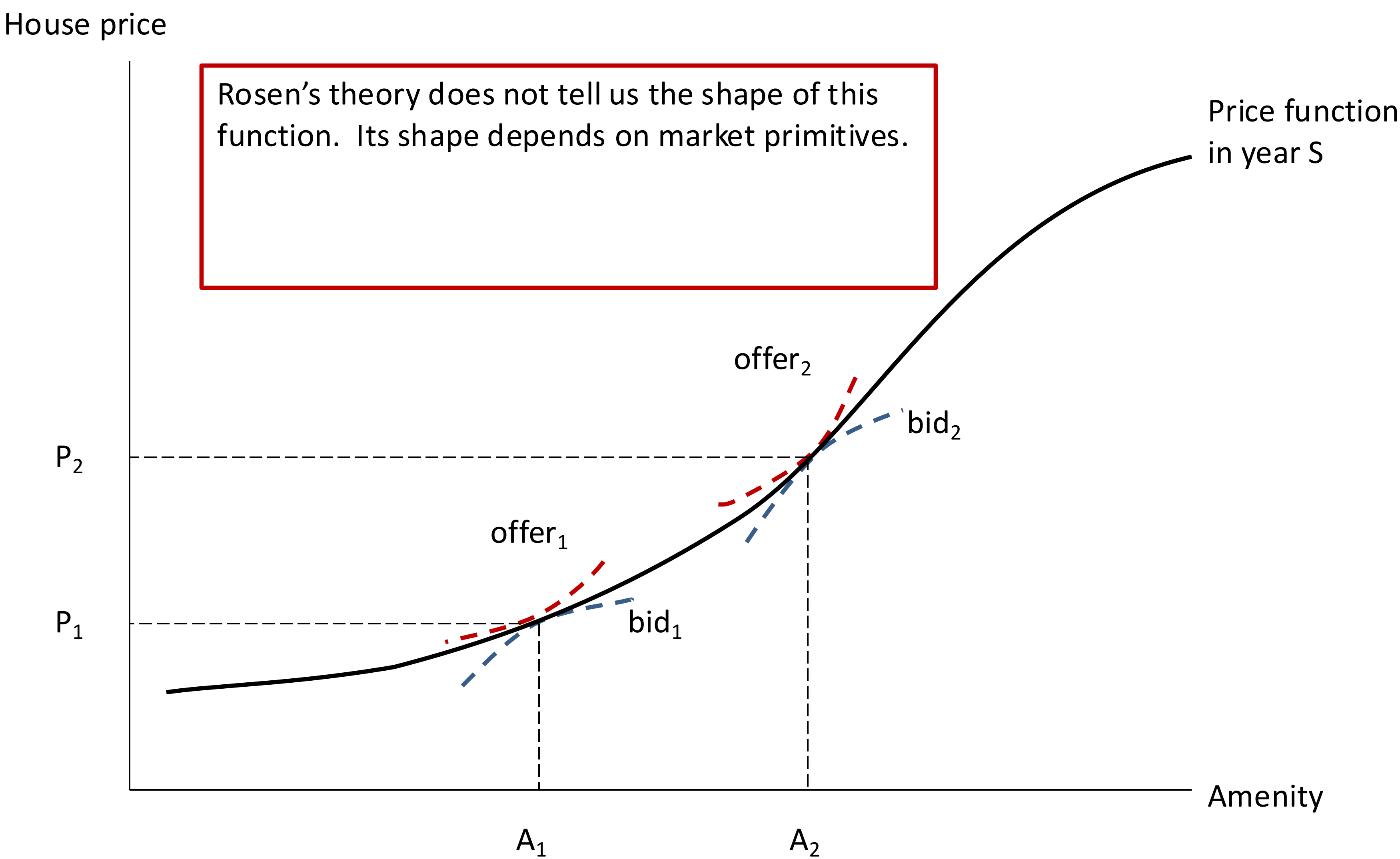
Best practice – match amenity data to houses at the spatiotemporal scale believed to affect location decisions and assess robustness

Potential issues to consider

- Buyer beliefs may be unknown and heterogenous (more on this later)
- Buyers may care about features of environmental quality not directly targeted by policy (e.g. water clarity versus ecosystem health)
- Beliefs may be based on past, present and/or future amenity levels (Bishop and Murphy, ReStat 2019)

Estimating MWTP: Functional Form

Rosen's theory does not tell us the shape of this function. Its shape depends on market primitives.



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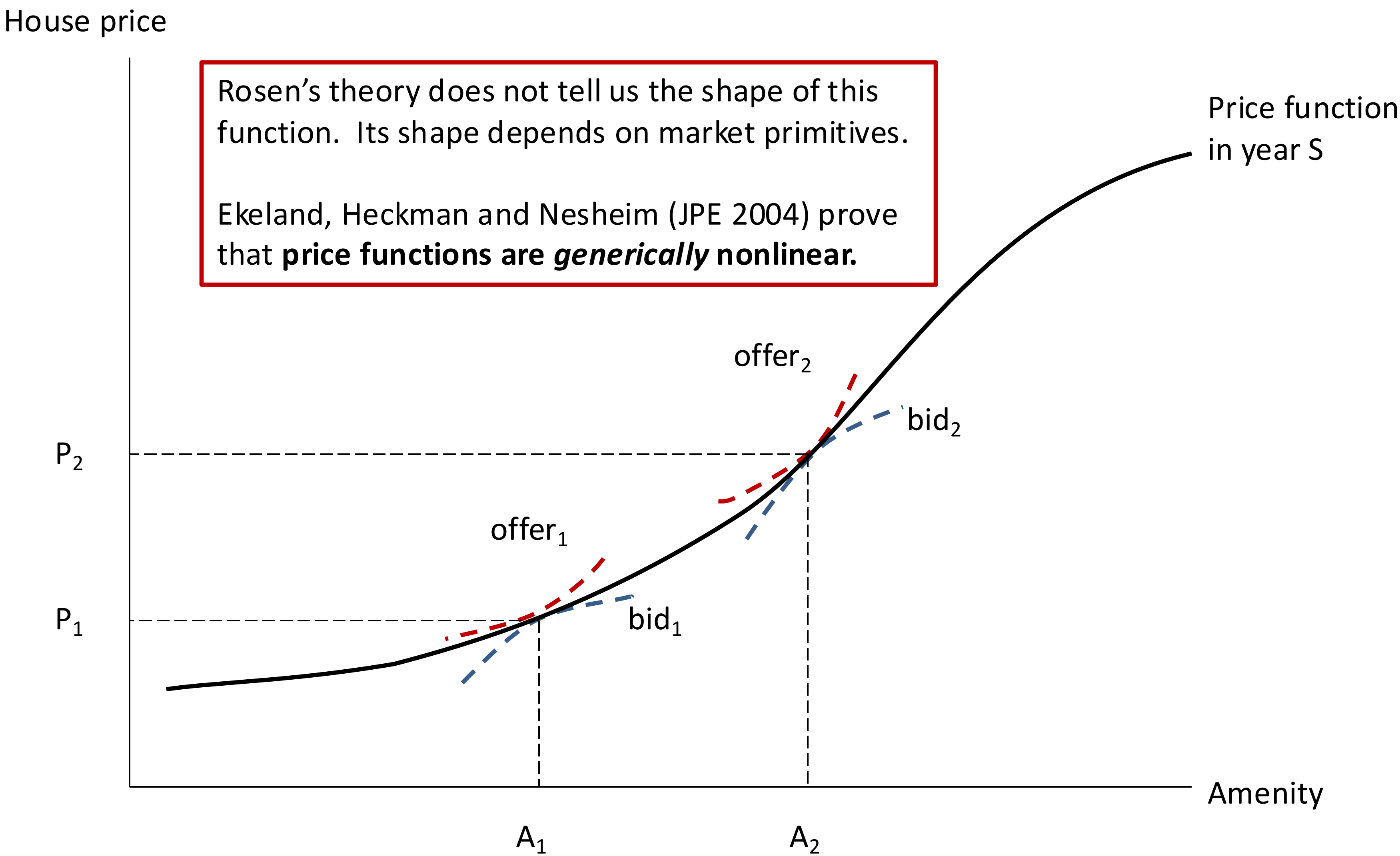
Ekeland, Heckman and Nesheim (JPE 2004) prove that **price functions are *generically* nonlinear.**



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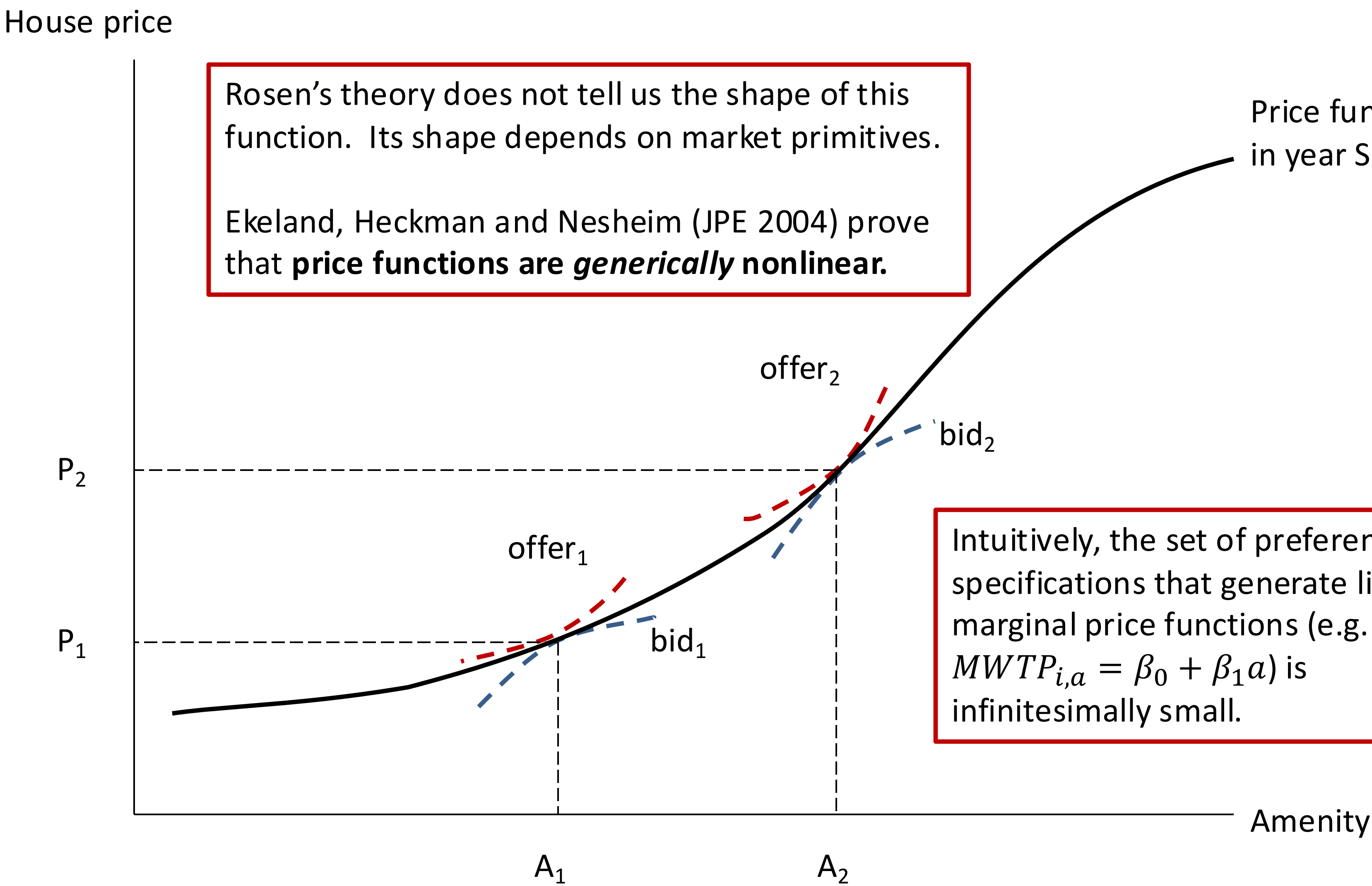

Intuitively, the set of preference specifications that generate linear marginal price functions (e.g. $MWTP_{i,a} = \beta_0 + \beta_1 a$) is infinitesimally small.

Estimating MWTP: Functional Form

<u>Best practice</u> – allow for nonlinearity in the shape of the price function

- Flexibility avoids the need to take a stance on the functional form of preferences (Ekeland, Heckman, and Nesheim JPE 2004)

- Econometric errors
  - Heteroskedasticity and spatial correlation can be addressed by using robust standard errors and clustering.
  - Spatial econometrics offers FGLS-type tradeoffs

Estimating MWTP: Functional Form

<u>Best practice</u> – allow for nonlinearity in the shape of the price function

$$log(p_j) = \beta_0 + \beta_1 a_j + \beta_2 X_j + \delta_{j \in k} + \varepsilon_j$$

$$log(p_j) = \beta_0 + \beta_1 log(a_j) + \beta_2 log(X_j) + \delta_{j \in k} + \varepsilon_j$$

Estimating MWTP: Functional Form

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Spatial fixed effects for
$k = 1, \dots, K$ areas

Estimating MWTP: Functional Form

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- Simple specifications above follow from Cropper, Deck and McConnell (RESTAT 1988) and Kuminoff, Parmeter and Pope (JEEM 2010)

- These specifications yield relatively accurate estimates for MWTP in theoretically-consistent Monte Carlo simulations of hedonic equilibria

Estimating MWTP: Omitted Variable Bias

Best practice – document transparent exogenous variation in amenity

- Common identification strategies
  - spatial dummy variables (e.g. Von Gravenitz JEEM 2018)
  - matching (e.g. Walls et al. JEEM 2017)
  - boundary discontinuity (e.g. Black QJE 1999)
  - instrumental variables (e.g. Chay and Greenstone JPE 2005)
  - repeat sales (e.g. Davis AER 2004)

- Econometric identification strategy conditions interpretation
  - spatial sample selection
  - price function changes

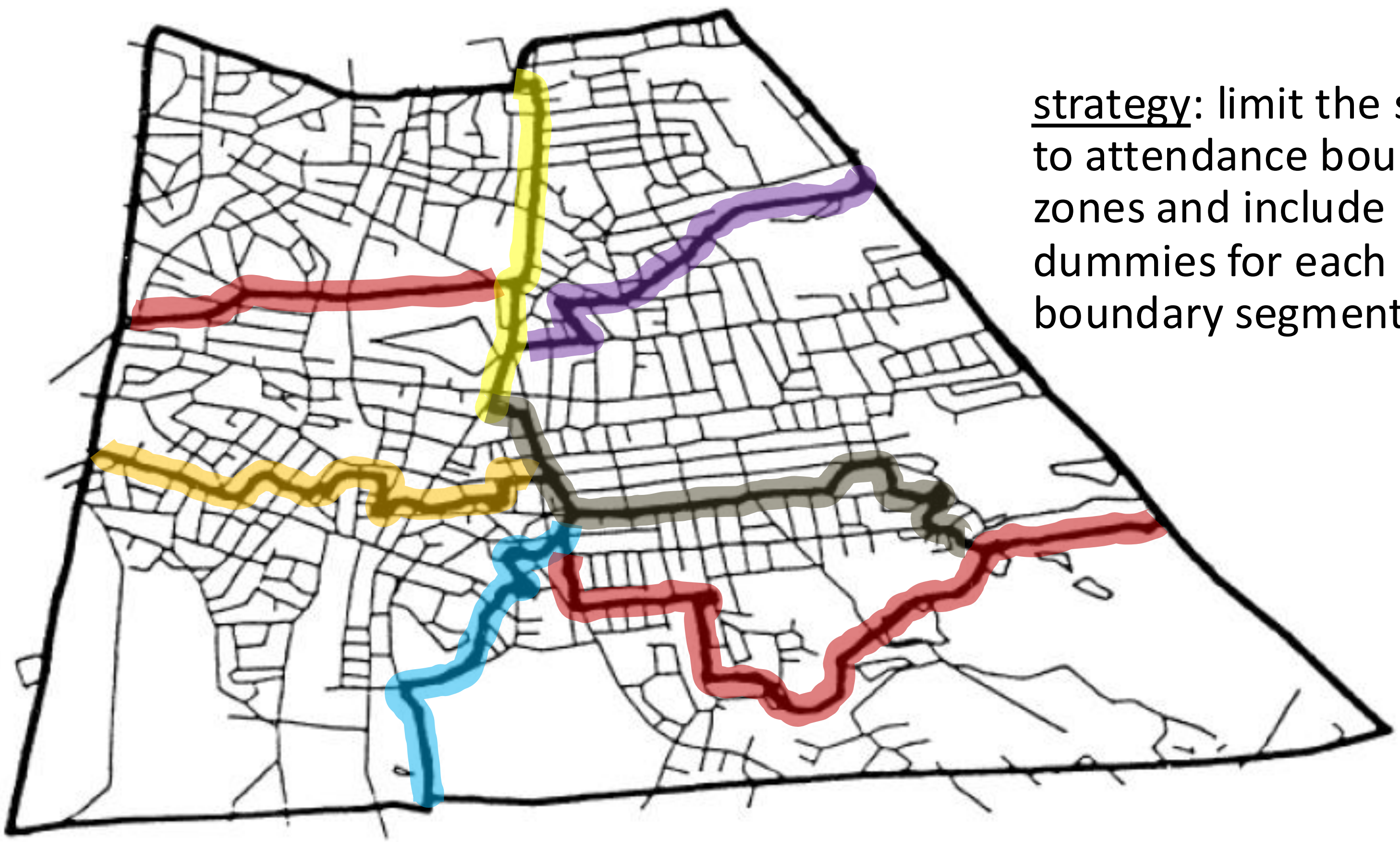
Example: Boundary Discontinuity Design (Black 1999)

Suppose we have data on house prices and characteristics, and school quality:

$$log(p_i) = \beta_0 + \underbrace{\beta_1 quality_i}_{\text{school quality}} + \underbrace{\beta_2 bedrooms_i + \cdots + \beta_k sqft_i}_{\text{physical characteristics}} + u_i$$

<u>Omitted variable problem</u>: u_i may include omitted amenities that are correlated with school quality and prices.

Example: Boundary Discontinuity Design (Black 1999)



<u>strategy</u>: limit the sample to attendance boundary zones and include dummies for each boundary segment

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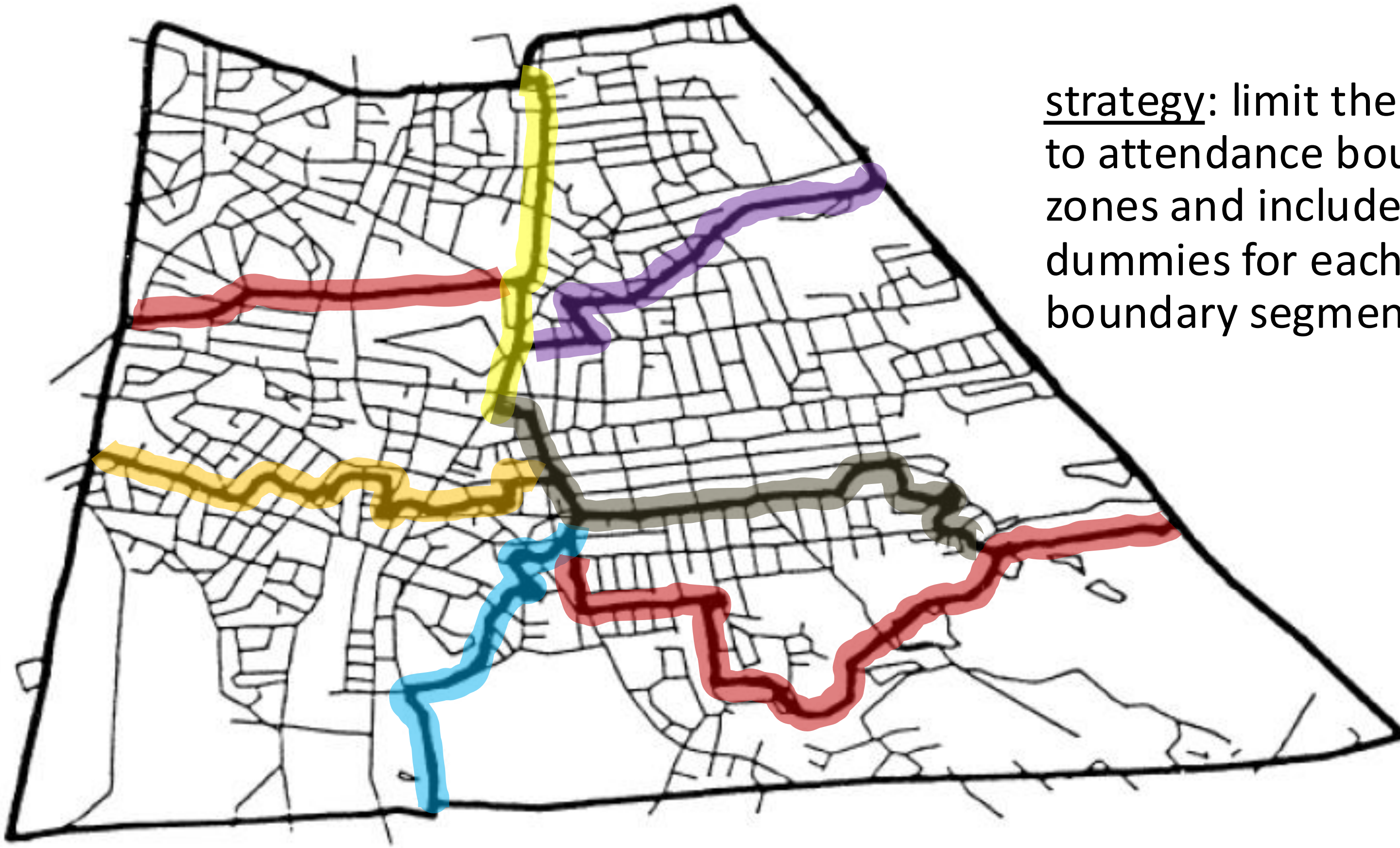

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$$log(p_i) = \beta_0 + \beta_1 \boldsymbol{school\ quality}_i + \beta_2 bedrooms_i + \beta_3 bathrooms_i + \beta_4 lotsize_i + \beta_5 sqft_i$$

$$+\beta_6 border1_i + \beta_7 border2_i + \cdots + \beta_k borderk_i + u_i$$

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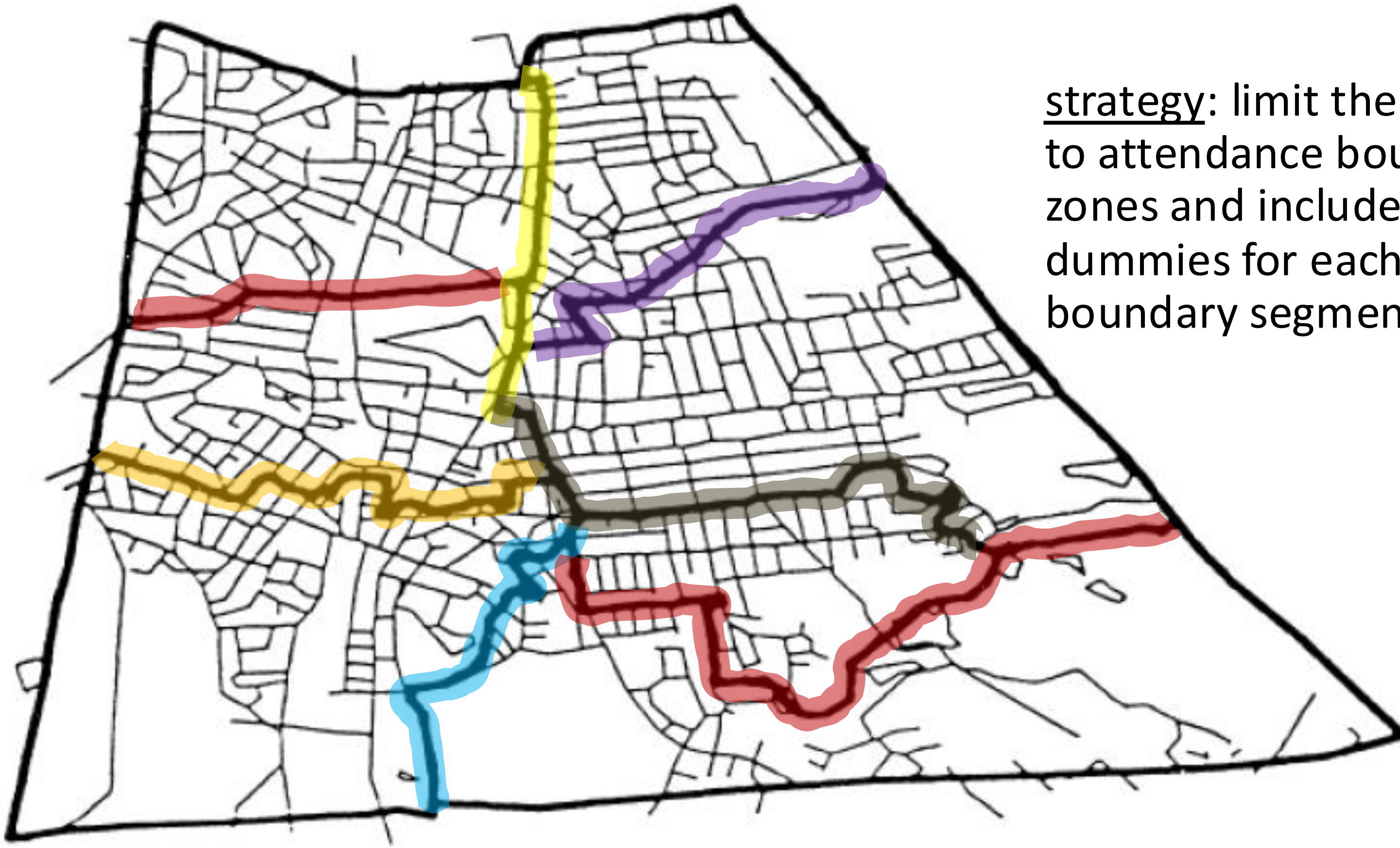

strategy: limit the sample to attendance boundary zones and include dummies for each boundary segment

- The border segment dummies absorb the price effects of omitted variables common to both sides of a border. This forces $\hat{\beta}_1$ to be identified by price changes as one steps across a border, all else constant. Other applications: flood zones, electricity prices.

Example: Boundary Discontinuity Design (Black 1999)

- Advantage of the quasi-experiment – reduces concerns about omitted variable bias
- Limitation – discards data outside boundary zones (i.e. all unshaded areas)

Example: Capitalization Effects

Period 1 price function: $log(p_1) = \beta_1 a_1 + \gamma_1 X_1 + \varepsilon_1$

Period 2 price function: $log(p_2) = \beta_2 a_2 + \gamma_2 X_2 + \varepsilon_2$

Example: Capitalization Effects

Period 1 price function: $log(p_1) = \beta_1 a_1 + \gamma_1 X_1 + \varepsilon_1$

Period 2 price function: $log(p_2) = \beta_2 a_2 + \gamma_2 X_2 + \varepsilon_2$

First-difference: $\Delta log(p) = \beta_2 a_2 - \beta_1 a_1 + \gamma_2 X_2 - \gamma_1 X_1 + \varepsilon_2 - \varepsilon_1$

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Capitalization model: $\Delta log(p) = \phi \Delta a + \delta \Delta X$

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- Instruments for Δa may be available (e.g. Chay and Greenstone JPE 2005)

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Capitalization model: $\Delta log(p) = \boldsymbol{\phi} \Delta a + \delta \Delta X$

- Instruments for Δa may be available (e.g. Chay and Greenstone JPE 2005)
- However, additional assumptions are needed for the amenity capitalization effect, $\boldsymbol{\phi}$, to identify MWTP (Kuminoff and Pope IER 2014, Banzhaf JPE 2021)

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- Instruments for Δa may be available (e.g. Chay and Greenstone JPE 2005)
- However, additional assumptions are needed for the amenity capitalization effect, ϕ, to identify MWTP (Kuminoff and Pope IER 2014, Banzhaf JPE 2021)
- For example, ϕ identifies MWTP if the shape of the price function is constant over the study period: $\beta_1 = \beta_2 = \phi$ and $\gamma_1 = \gamma_2 = \delta$

Distributional Effects

WHO BENEFITS FROM ENVIRONMENTAL REGULATION? EVIDENCE FROM THE CLEAN AIR ACT AMENDMENTS

Antonio Bento, Matthew Freedman, and Corey Lang*

Abstract—Using geographically disaggregated data and exploiting an instrumental variable strategy, we show that contrary to conventional wisdom, the benefits of the 1990 Clean Air Act Amendments (CAAA) were progressive. The CAAA created incentives for local regulators to target the initially dirtiest areas for cleanup, creating heterogeneity in the incidence of air quality improvements that favored lower-income households. Based on house price appreciation, households in the lowest quintile of the income distribution received annual benefits from the program equal to 0.3% of their income on average during the 1990s, over twice as much as those in the highest quintile.

I. Introduction

CONVENTIONAL wisdom holds that environmental policies are regressive (Fullerton, 2011; Banzhaf, 2011; Bento, 2013). This is in part because the costs of these policies tend to fall disproportionately on lower-income households, which generally spend a higher fraction of their income on energy-intensive goods and are employed in larger numbers in energy-related industries. There is also some evidence that the benefits of environmental policies tend to accrue mainly to higher-income households. Higher-income households are more likely to be homeowners, and thus are more likely to reap the benefits of any capitalization of environmental improvements into property values.

The purpose of this paper is to carefully explore the distribution of the benefits of the 1990 Clean Air Act Amendments (CAAA), an important component in understanding the overall distributional impacts of the program. First enacted in 1970, the Clean Air Act established standards for the ambient concentrations of criteria pollutants with the goal of improving air quality and protecting human health. Following amendments in 1990, the act began regulating particulates less than 10 micrometers in diameter (PM_{10}), for which the negative health effects were deemed particularly severe. A county is designated to be out of attainment with the standard if at least one of the monitors within the county had concentrations of PM_{10} exceeding the standard.

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* Bento: University of Southern California and NBER; Freedman: Drexel University; Lang: University of Rhode Island.

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A supplemental appendix is available online at http://www.mitpressjournals.org/doi/suppl/10.1162/REST_a_00493.

Despite being the most ambitious federal environmental legislation to date, the existing literature provides little evidence on the extent to which the benefits in air quality improvements induced by the Clean Air Act and its amendments accrued to different segments of the population. Several studies that have attempted to measure the distribution of the benefits of the program have used locational equilibrium models and focused on a limited number of metropolitan areas, emphasizing within-metropolitan area differences in the distribution of benefits that result from general equilibrium adjustments in housing prices (Sieg et al., 2004; Tra, 2010). Other studies have examined the aggregate impacts on certain subgroups of the population, such as renters and homeowners (Grainger, 2012), but have not accounted for important differences in the impacts of the program across households within these subgroups.

We provide compelling new evidence that the benefits of the 1990 CAAA, measured by capitalization of air quality improvements in housing prices and rents, were in fact progressive, contrary to what these past studies suggest. First, we demonstrate that the air quality improvements induced by the 1990 CAAA were highly localized, as local regulators had incentives to target the areas around nonattainment monitors as a strategy to ensure their counties were in attainment with federal standards. Second, we estimate capitalization of the air quality changes induced by the program. For homes located within 5 miles of a nonattainment monitor, which we show to be owned by relatively low-income households on average, our estimate of the elasticity of house prices with respect to PM_{10} reductions is about -0.6. For homes located farther away, which tend to be owned by more affluent households, we detect sharply less appreciation attributable to the 1990 CAAA. Rental prices also appear to have increased in a localized fashion, but the capitalization of air quality improvements into rents is substantially smaller and less consistent than for housing prices.

Consequently, lower-income homeowners tended to enjoy the greatest benefits from the 1990 CAAA, as these were the homeowners located in areas that experienced the largest improvements in air quality. Based on house price appreciation, households in the lowest quintile of the income distribution received annual benefits from the program equal to 0.3% of their income on average during the 1990s, over twice as much as those in the highest quintile. Importantly, though, while poorer households living close to monitors benefited greatly from the reductions in pollution induced by the 1990 CAAA, a larger number of households living farther from monitors also benefited, but each to a smaller extent.

Our main empirical challenge is to estimate the causal effect of declines in PM_{10} on housing prices. To do this, we

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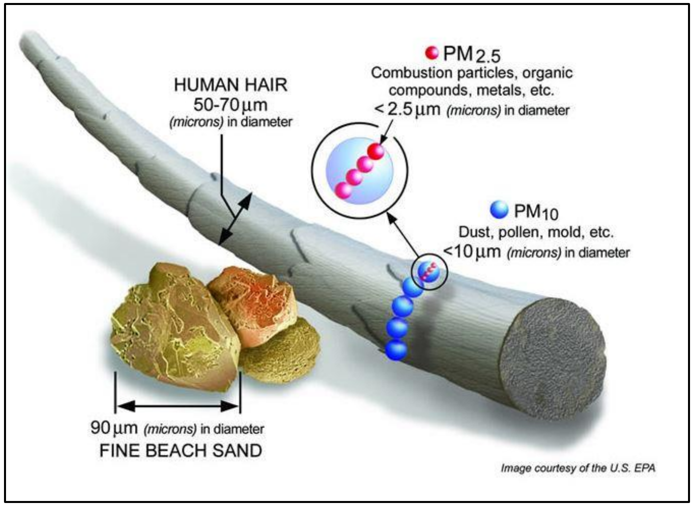


- Bento, Freedman and Lang (2015) apply the Chay-Greenstone IV-FD model to EPA's regulation of PM_{10} in 1990 and analyze distributional implications.

Distributional Effects

$$\Delta PM_i = \varphi N_i + \Delta \mathbf{X}_i \Pi + \mu_i,$$

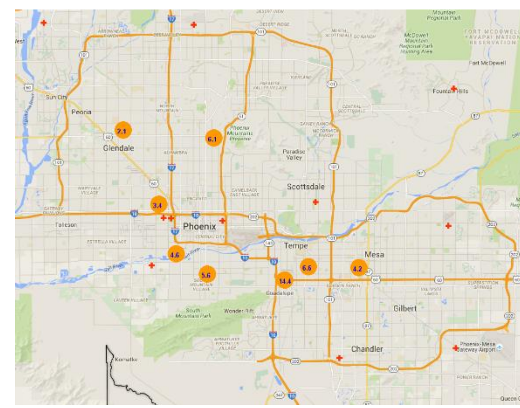
$$\Delta p_i = \gamma N_i + \Delta \mathbf{X}_i \Omega + v_i,$$

- <u>Sample coverage</u>: about one third of the U.S. population living in counties with good panel data from air quality monitors.

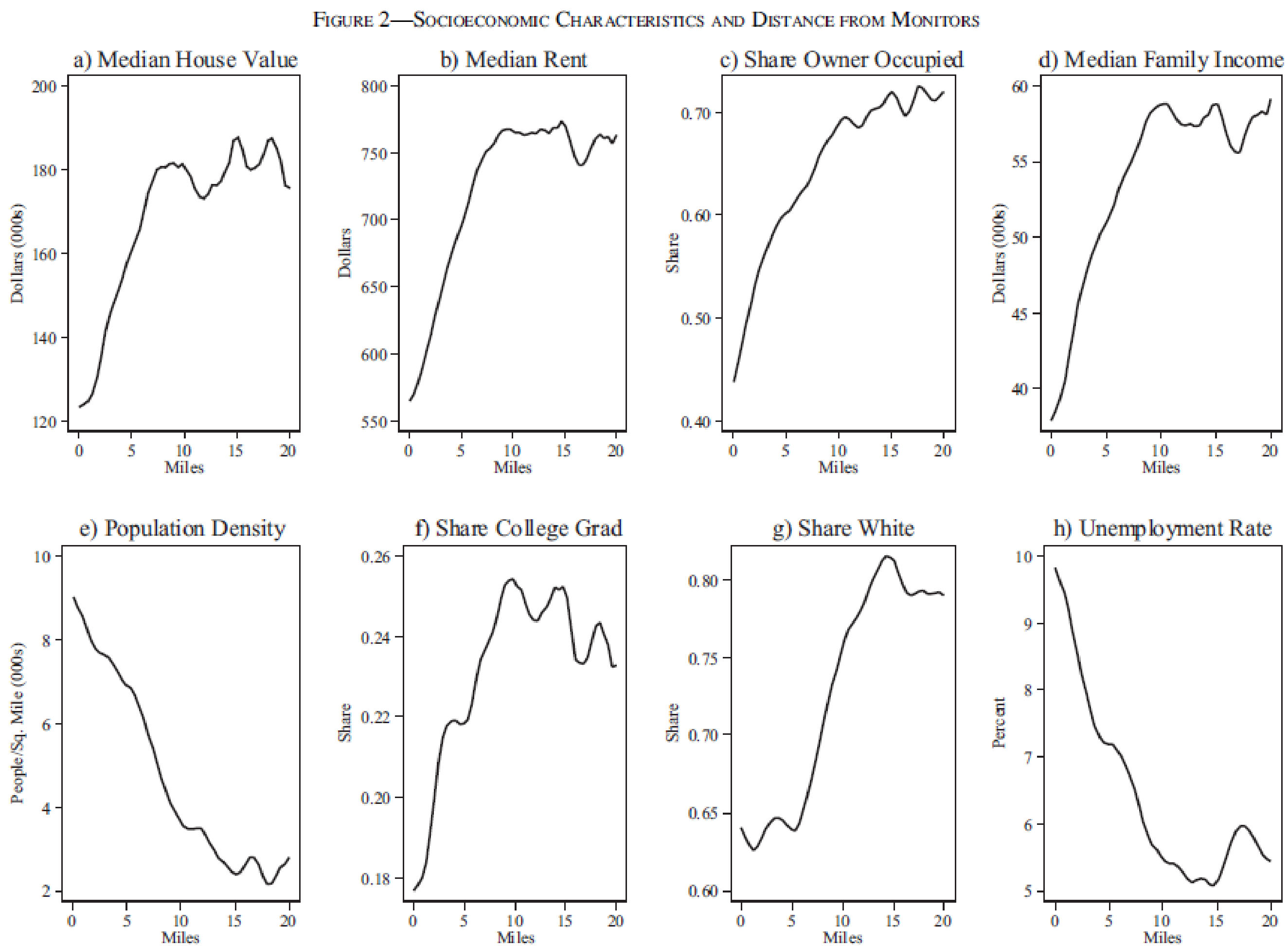
TABLE 2—FIRST-STAGE RESULTS

	(1)	(2)
Monitor nonattainment	−11.85***	−9.71***
	(2.71)	(2.67)
County nonattainment		−2.79***
		(0.81)
F-statistic	19.17	15.37
R^2	0.29	0.29
Sample size	375	375

The dependent variable is the change in PM_{10} concentration. Both regressions include the full set of controls listed in table A2 in the online appendix and use the ratio instruments constructed from 1992 to 1997. Standard errors are shown in parentheses and are estimated using the Eicker-White formula to correct for heteroskedasticity and are clustered at the county level. Significant at *10%, **5%, ***1%.



Distributional Effects

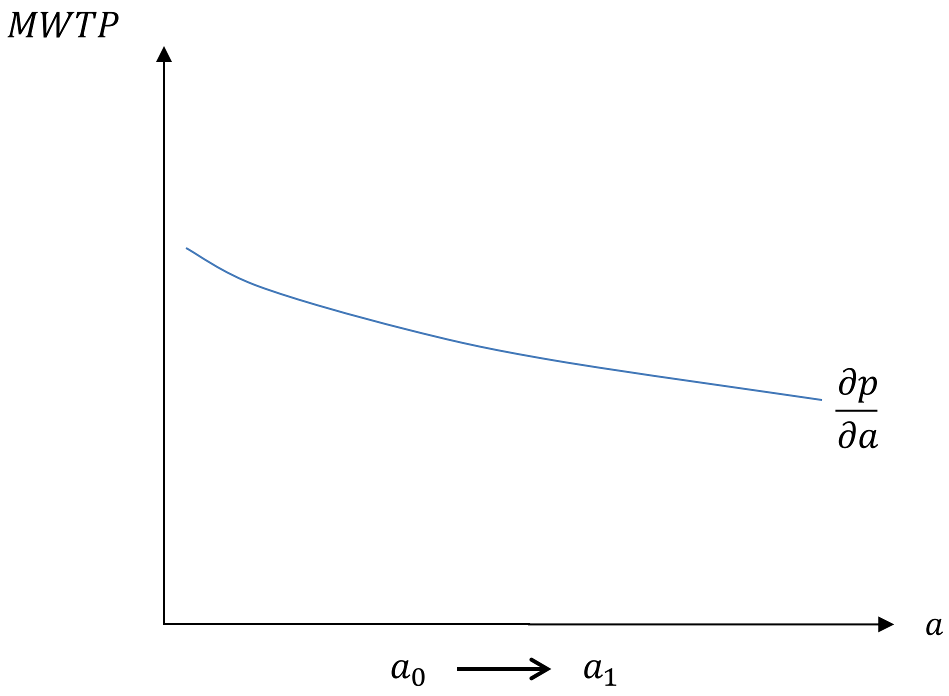


- Capitalization effects were largest for homeowners living close to monitors

Other Amenity Capitalization Studies

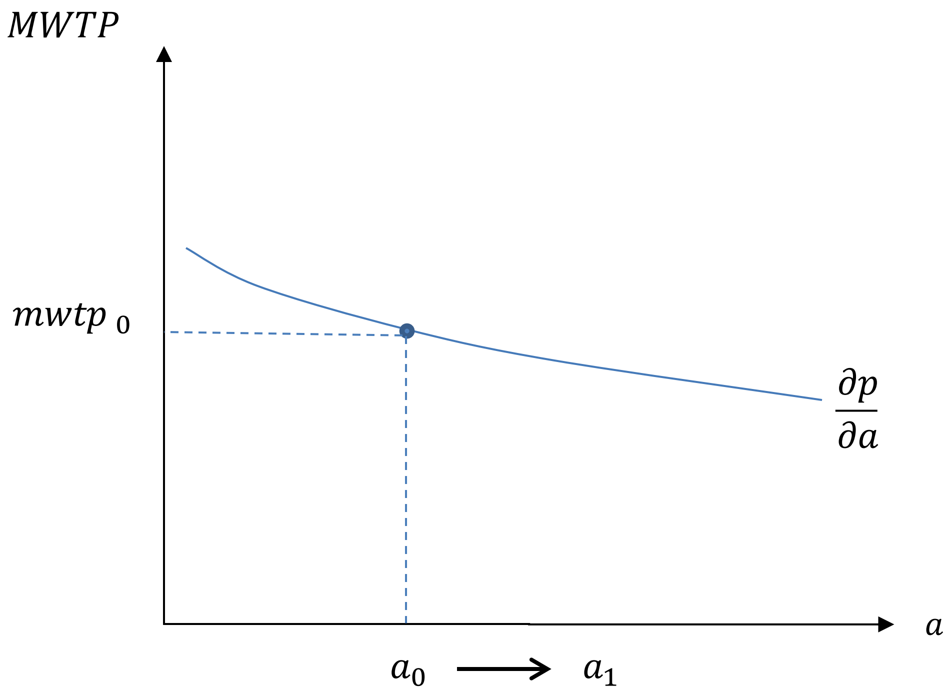
Amenity	Authors	Year	Journal
pediatric leukemia	Davis	2004	AER
air pollution	Chay-Greenstone	2005	JPE
hazardous waste	Greenstone-Gallagher	2008	QJE
crime	Linden-Rockoff	2008	AER
open space	Bin et al.	2008	AJAE
invasive species	Horsch-Lewis	2009	LAND
low income housing credits	Baum-Snow & Marion	2009	J.PUB.E
education grants	Cellini et al.	2010	QJE
power plants	Davis	2011	REStat
value of a statistical life	Kneisner et al.	2012	REStat
toxic polluting facilities	Currie et al.	2014	AER
fracking externalities	Muhlenbachs et al.	2015	AER
water pollution	Kaiser-Shaprio	2018	QJE
air pollution	Sager-Singer	2024	AEJ-Policy

Using MWTP for Policy Evaluation



Suppose we want to evaluate welfare for a counterfactual increase in the amenity from a_0 to a_1

Using MWTP for Policy Evaluation



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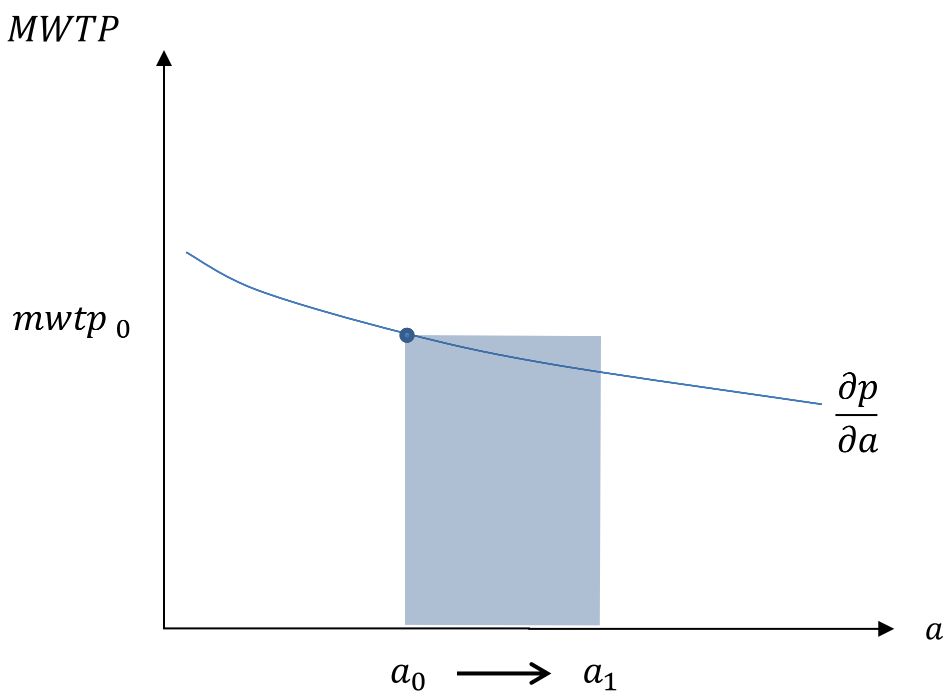
Using MWTP for Policy Evaluation



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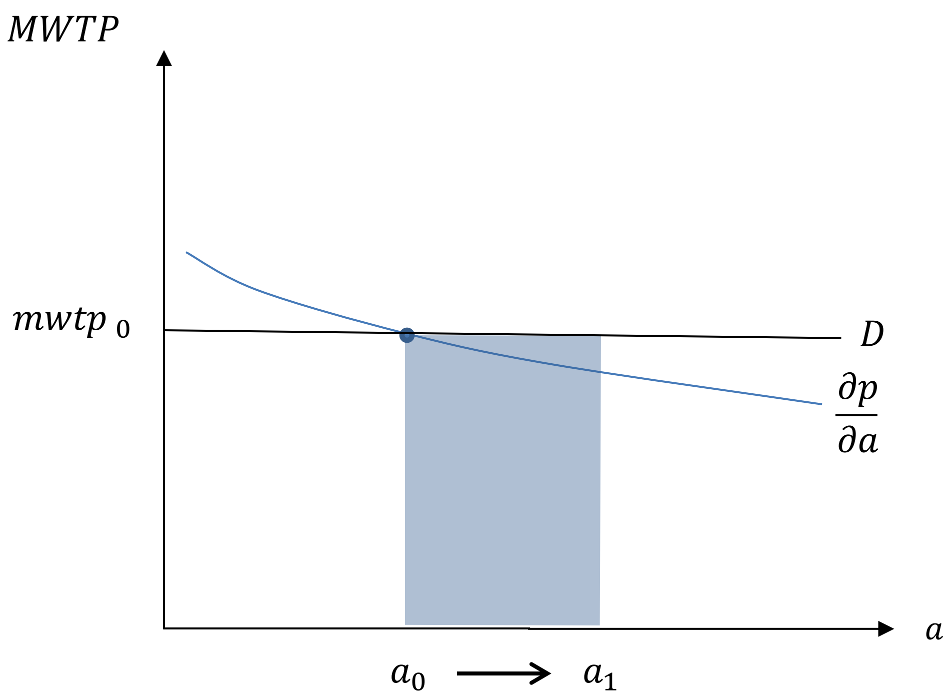
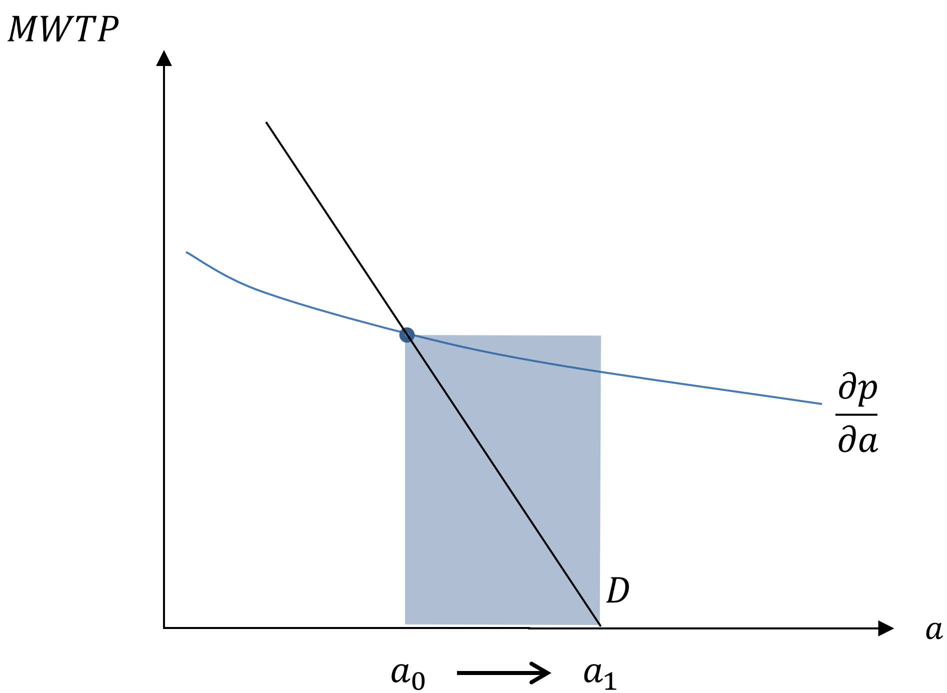
Using MWTP for Policy Evaluation



Provides an exact welfare measure if the consumer's demand curve is perfectly elastic

Using MWTP for Policy Evaluation



Provides an approximation to welfare if demand is less than perfectly elastic, where the approximation error varies with the shape of the demand curve and the size of the change in a.

Hedonic Price Functions: Summary

- Powerful microeconometric framework for identifying consumers' MWTP for non-market attributes of differentiated goods
- *Marginal* WTP can be useful for some policy questions
- Variety of strategies for mitigating omitted variable bias
- Interpretation of results depends on empirical research design
- Not ideal for evaluating counterfactual policies that would have large effects or cause people and markets to adjust (i.e. sorting)

Outline

1. The hedonic property value model

2. Best practices for using price functions to estimate MWTP

3. **Modeling sorting behavior**

   - identification and estimation

   - validation

   - extensions: dynamics, heterogeneous beliefs

4. Questions / Discussion

Slides: https://nickkuminoff.github.io/webpage/hedonic.pdf

A Unified Framework for Measuring Preferences for Schools and Neighborhoods

Patrick Bayer

Duke University and National Bureau of Economic Research

Fernando Ferreira

University of Pennsylvania

Robert McMillan

University of Toronto and National Bureau of Economic Research

This paper develops a framework for estimating household preferences for school and neighborhood attributes in the presence of sorting. It embeds a boundary discontinuity design in a heterogeneous residential choice model, addressing the endogeneity of school and neighborhood characteristics. The model is estimated using restricted-access Census data from a large metropolitan area, yielding a number

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[*Journal of Political Economy*, 2007, vol. 115, no. 4]

- Tractable static model of sorting
- WTP for counterfactual policies
- Applications to air quality, open space, climate change...
- Can address endogeneity of housing prices and amenities
- Validation (Galiani et al. 2015)
- Dynamic extension (Bayer et al. 2016)
- Potential extension to heterogeneous beliefs (Leggett ERE 2002)

- Epple and Sieg (JPE 1999) and Sieg et al. (IER 2004) provide an alternative framework

Sorting Models: Identification and Estimation

- Basic idea – use a McFadden (1978) style random utility model with a spatial analog to BLP instruments to explain observed housing choices

$$V_{i,j} = \alpha_h^i h_j + \alpha_g^i g_j + \alpha_p^i p_j + \xi_j + \varepsilon_j^i,$$

Sorting Models: Identification and Estimation

- Basic idea – use a McFadden (1978) style random utility model with a spatial analog to BLP instruments to explain observed housing choices

household i's utility from house j

$$V_{i,j} = \alpha_h^i h_j + \alpha_g^i g_j + \alpha_p^i p_j + \xi_j + \varepsilon_j^i,$$

house characteristics (e.g. bedrooms, bathrooms, square feet of living space, crime)

amenity

price

unobserved characteristics

idiosyncratic taste shock

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$$\text{where } \boldsymbol{\alpha_g^i} = \alpha_{0,g} + \sum_{r=1}^{R} \alpha_{r,g} d_r^i$$

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Household demographics
(e.g. income, education, age,
number of children, race,
medical conditions)

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$$\boldsymbol{\varepsilon_j^i} \sim \text{iid type I extreme value}$$

- Use type I EV assumption to define the probability that each household type, d^i, occupies each house type, j. Choose parameters that match these probabilities to market shares.

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$$\varepsilon_j^i \sim \text{iid type I extreme value}$$

Note: identification requires multiple houses of each ***j*** type (e.g. 3 bedroom, 2 bathroom, in a given neighborhood)

- Use type I EV assumption to define the probability that each household type, d^i, occupies each **house type, *j***. Choose parameters that match these probabilities to market shares.

Sorting Models: Identification and Estimation

- Estimation begins by dividing utility into mean utility, observed heterogeneity, and unobserved heterogeneity:

$$V_{i,j} = \delta_j + \lambda_j^i + \varepsilon_j^i,$$

$$\text{where } \delta_j = \alpha_{0,h} h_j + \alpha_{0,g} g_j + \alpha_{0,p} p_j + \xi_j$$

$$\text{and } \lambda_j^i = \sum_{r=1}^{R} \left(\alpha_{r,h} d_r^i\right) h_j + \sum_{r=1}^{R} \left(\alpha_{r,g} d_r^i\right) g_j + \sum_{r=1}^{R} \left(\alpha_{r,p} d_r^i\right) p_j$$

- Type I EV assumption gives logit expression for choice probabilities:

$$prob_j^i = \frac{exp\left(\delta_j + \lambda_j^i\right)}{\sum_k exp\left(\delta_k + \lambda_k^i\right)}$$

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Stage 1: use maximum likelihood with Berry (1994) contraction mapping to estimate δ_j and heterogenous preferences

$$prob_j^i = \frac{exp\left(\delta_j + \lambda_j^i\right)}{\sum_k exp\left(\delta_k + \lambda_k^i\right)}$$

Stage 2: use $\hat{\delta}_j$ and 2SLS to estimate mean utility parameters

Sorting Models: Identification and Estimation

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Sorting Models: Identification and Estimation

$$V_{i,j} = \widehat{\boldsymbol{\delta}}_{\boldsymbol{j}} + \lambda_j^i + \varepsilon_j^i,$$

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<u>Identification issue #1</u>: endogenous amenity: $\mathrm{E}\left[\xi_j \middle| g_j\right] \neq 0$

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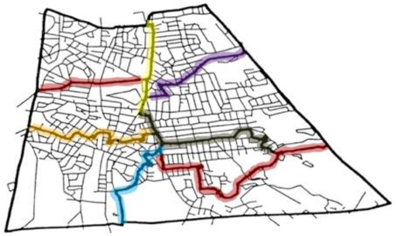
Identification issue #1: endogenous amenity: $\mathrm{E}\left[\xi_j \middle| g_j\right] \neq 0$

Solution: follow Black (1999) in cutting sample to boundary zones and add **boundary fixed effects** to the regression



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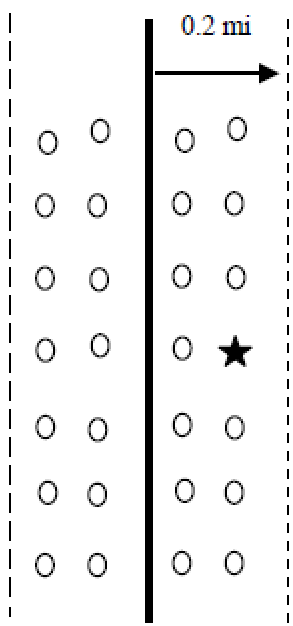
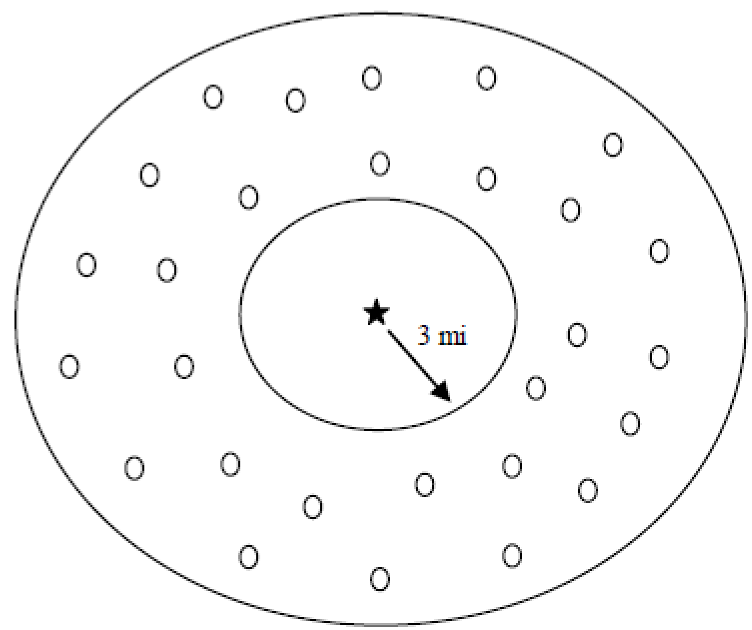
Identification issue #2: endogenous prices: $\mathrm{E}\left[\xi_j \middle| p_j\right] \neq 0$

Solution: adapt Berry, Levinson and Pakes (1995) in instrumenting for p_j using non-price attributes of other houses (a.k.a. 'donut instruments')

$$\hat{\delta}_j = \alpha_{0,h} h_j + \alpha_{0,g} g_j + \alpha_{0,p} p_j + BFE_j + \xi_j$$

<u>Solution</u>: adapt Berry, Levinson and Pakes (1995) in instrumenting for p_j using non-price attributes of other houses (a.k.a. ‘donut instruments’)





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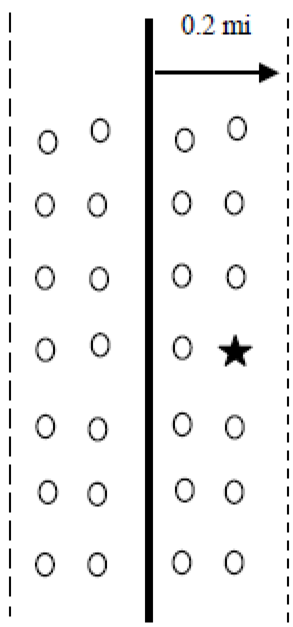
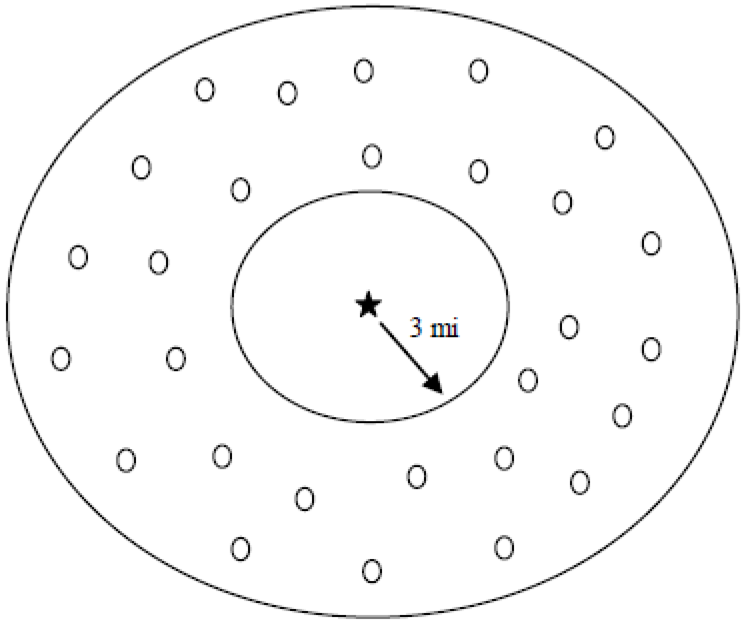
Solution: adapt Berry, Levinson and Pakes (1995) in instrumenting for p_j using non-price attributes of other houses (a.k.a. 'donut instruments')

relevance – in equilibrium, p_j depends on attributes of all houses

validity – attributes of distant houses are uncorrelated with ξ_j





$$\hat{\delta}_j = \alpha_{0,h} h_j + \alpha_{0,g} g_j + \alpha_{0,p} p_j + BFE_j + \xi_j$$

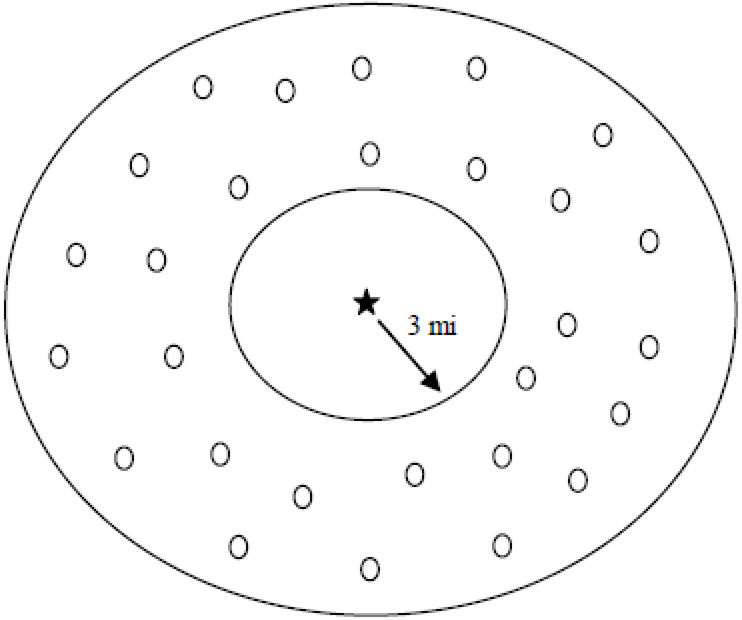
Solution: adapt Berry, Levinson and Pakes (1995) in instrumenting for p_j using **non-price attributes of other houses** (a.k.a. 'donut instruments')

relevance – in equilibrium, p_j depends on attributes of all houses

validity – attributes of distant houses are uncorrelated with ξ_j

Instruments used

share of land in residential, commercial, industrial, parks, etc.



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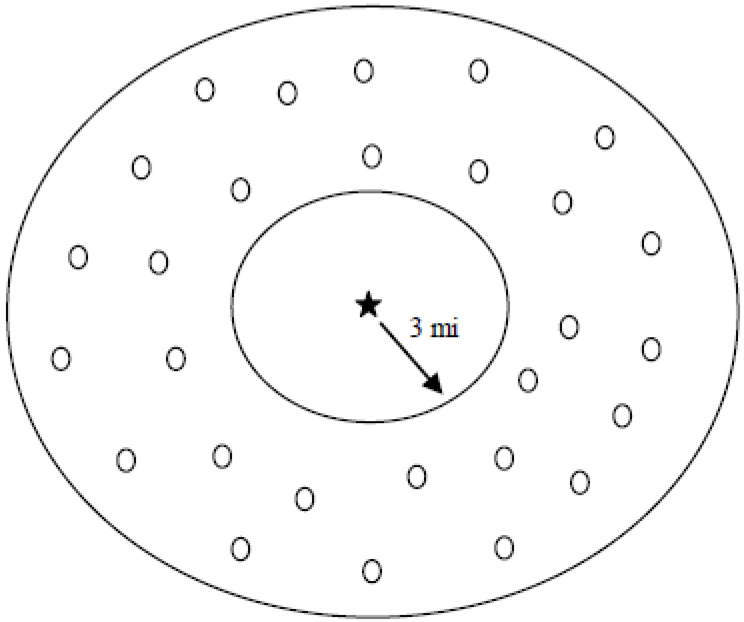


Consistency and asymptotic normality details:

- Bayer et al. (2007) appendix
- Berry, Linton and Pakes (RESTUD 2004)
- McFadden (1978)

Sorting Models: Identification and Estimation

- $V_{i,j} = \alpha_h^i h_j + \alpha_g^i g_j + \alpha_p^i p_j + \xi_j + \varepsilon_j^i$

- $MWTP = \frac{\partial V/\partial g}{\partial V/\partial p}$ (similar for hedonic and sorting models in Bayer et al.)

- $E[WTP] = \frac{1}{\alpha^i}\left[ln \sum_{C^1} exp\left(V_{i,j}\right) - ln \sum_{C^0} exp\left(V_{i,j}\right)\right]$

- Can use choice probabilities to predict migration flows

- For derivations of welfare measures see Small & Rosen (ECMA 1981), Bockstael and McConnell (2007) book or Train (2003) book

Do Assumptions Invalidate Sorting Model Predictions?

Parametric form assumptions:

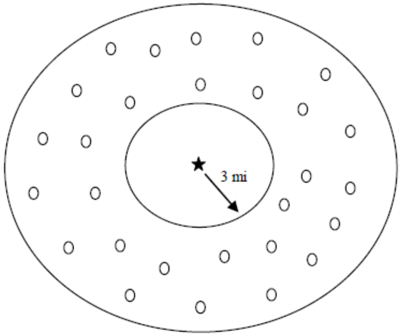
$$V_{i,j} = \alpha_h^i h_j + \alpha_g^i g_j + \alpha_p^i p_j + \xi_j + \varepsilon_j^i,$$

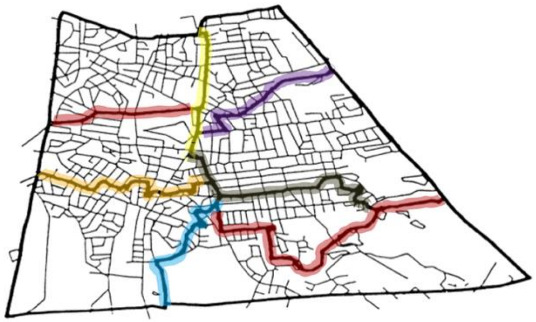
$$\text{where } \alpha_g^i = \alpha_{0,g} + \sum_{r=1}^{R} \alpha_{r,g} d_r^i$$

Distributional assumptions:

$\varepsilon_j^i \sim$ iid type I extreme value $\longrightarrow$ $prob_j^i = \dfrac{exp(\delta_j + \lambda_j^i)}{\sum_k exp(\delta_k + \lambda_k^i)}$

Spatial assumptions:





Sorting Models: Validation

American Economic Review 2015, 105(11): 3385–3415
http://dx.doi.org/10.1257/aer.20120737

Estimating Neighborhood Choice Models: Lessons from a Housing Assistance Experiment[†]

By Sebastian Galiani, Alvin Murphy, and Juan Pantano*

We use data from a housing-assistance experiment to estimate a model of neighborhood choice. The experimental variation effectively randomizes the rents which households face and helps identify a key structural parameter. Access to two randomly selected treatment groups and a control group allows for out-of-sample validation of the model. We simulate the effects of changing the subsidy-use constraints implemented in the actual experiment. We find that restricting subsidies to even lower poverty neighborhoods would substantially reduce take-up and actually increase average exposure to poverty. Furthermore, adding restrictions based on neighborhood racial composition would not change average exposure to either race or poverty. (*JEL* I32, I38, R23, R38)

Sorting models have been used extensively in economics to model household location decisions. Building on earlier theoretical work,[1] there has been a large recent empirical literature that employs the sorting framework to estimate preferences and the marginal willingness to pay for a host of public goods and amenities such as school quality, crime, pollution, and the attributes of one's neighbors.[2] These

* Galiani: Department of Economics, University of Maryland, Tydings Hall, College Park, MD 20742 (e-mail: galiani@econ.umd.edu); Murphy: Department of Economics, Arizona State University, PO Box 879801, Tempe, AZ 85287 (e-mail: Alvin.Murphy@asu.edu); Pantano: Department of Economics, Washington University in St. Louis, Campus Box 1208, One Brookings Drive, Saint Louis, MO 63130 (e-mail: pantano@wustl.edu). We thank Brian Feld, Raul Sanchez, Ivan Torre, Bo Wang, and Dan Weiss for their valuable research assistance. We also thank David Albouy, Pat Bayer, Kelly Bishop, Flavio Cuhna, Dennis Epple, Limor Golan, Hanming Fang, Fernando Ferreira, Maria Marta Ferreyra, Judy Geyer, Vernon Henderson, Paul Joice, Matt Kahn, Jeff Kling, Nick Kuminoff, Maurizio Mazzoco, Costas Meghir, Steve Ross, Holger Sieg, Paulo Somaini, Kerry Smith, Chris Taber, Steve Tadelis, Giorgio Topa, Matt Wiswall, Ken Wolpin, two anonymous referees, conference and seminar participants at UPenn, New York Fed, ITAM, Oxford, Vanderbilt, Collegio Carlo Alberto, Tsinghua University, Pompeu Fabra, Toulouse, Cowles Foundation, NBER, HULM, Universidad de San Andres, Rimini, Pittsburgh, UIC, Cleveland Fed, Arizona State University, Xiamen University, 2012 Summer Meetings of the Econometric Society in Evanston, IL, and 2013 ASSA Meetings in San Diego, CA for helpful comments. Funding from the Center for Social Development and the Weidenbaum Center, both at Washington University in St. Louis, is greatly appreciated. Data used in this article was obtained through restricted-access data use agreements with the Inter-University Consortium for Political and Social Research (ICPSR) and the US Department of Housing and Urban Development (HUD). The views in this article do not necessarily reflect those of HUD. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

† Go to http://dx.doi.org/10.1257/aer.20120737 to visit the article page for additional materials and author disclosure statement(s).

[1] For important theoretical contributions, see Ellickson (1971); Epple, Filimon, and Romer (1984); Epple and Romer (1991); Epple and Romano (1998); and Nechyba (1999, 2000).

[2] See, among others, Epple and Sieg (1999); Sieg et al. (2004); Bayer, McMillan, and Rueben (2004); Bayer, Ferreira, and McMillan (2007); Ferreyra (2007); Walsh (2007); and Kuminoff (2012).

- Galiani, Murphy and Pantano (AER 2015) use an RCT to help identify a sorting model and test its predictions
- Test model's ability to predict migration-based outcomes that matter to policymakers
- <u>Context</u>: moving-to-opportunity experiments conducted by US Department of Housing and Urban Development offered randomly-assigned subsidies to help low-income families move from high-poverty neighborhoods to lower-poverty neighborhoods.
- <u>Note</u>: higher-poverty neighborhoods tend to have higher crime, fewer job opportunities, and lower environmental quality.

Random assignment to 3 groups

4,608 eligible families in public housing

Low-Poverty Voucher Group (LPV) (N = 1,800)
Offered restricted Section 8 voucher + mobility counseling
47% Leased up (N = 864)

Section 8 Group (S8) (N = 1,350)
Offered conventional Section 8 voucher
68% Leased up (N = 918)

Control Group (C) (N = 1,400)
No voucher, existing programs

Sorting Models: Validation

- Data from 1994-1998 track initial location (Census tract), group assignment, final location, household demographics, and neighborhood characteristics

TABLE 1—MTO DATA DESCRIPTIVE STATISTICS

	Control	Experimental	Section 8	Total
White	0.07	0.11	0.10	0.09
Household income ($1,000s)	11.8	11.9	11.3	11.7
Never married	0.63	0.64	0.69	0.65
Household size	3.38	3.07	3.26	3.23
Applied to Section 8 before	0.56	0.52	0.61	0.56
Moved three times before	0.15	0.15	0.15	0.15
Dissatisfied with neighborhood	0.30	0.33	0.27	0.30
Observations	165	204	172	541

Notes: Final analysis sample from Boston. Single headed households enrolled in the MTO demonstration. Variables in the table are measured at baseline. Annual household income in 1,000s of 1997 US$ includes welfare payments for those on welfare and estimated labor income for those working. See text for details.

Sorting Models: Validation

- Identification and estimation is very similar to Bayer et al. (2007) with two modifications:

$$V_{i,j} = \alpha_h^i h_j + \alpha_g^i g_j + \alpha_p^i p_j^i + \lambda_{ij} + \xi_j + \varepsilon_j^i,$$

where $\lambda_{ij} = \lambda_0 + \lambda_1 I\{mobility\ counseling\}$,

and p_j^i varies with random group assignment

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and p_j^i varies with random group assignment

- Estimation uses data from the control group and the experimental low-poverty voucher treatment.

- The unrestricted voucher treatment is held out for external validation. It is nested by the estimated model.

Sorting Models: Validation

- Fitted choice probabilities replicate in-sample amenity exposures (poverty rate, school quality, percent white, distance to jobs)

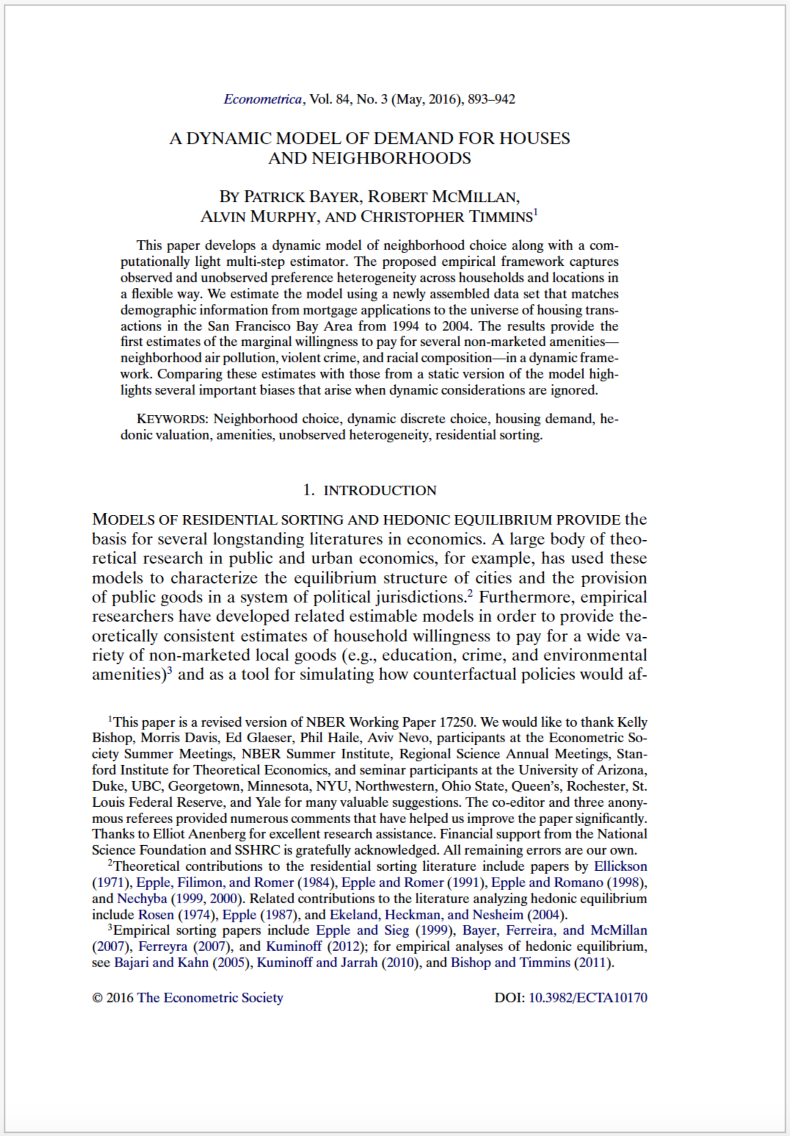
	Data		Model	
	0 Control	1 Exp	0 Control	1 Exp
Unconditional on move using the subsidy				
Percent who move	0.29	0.65	0.29	0.65
Mean poverty rate	0.37	0.20	0.34	0.21
Mean percent white	0.32	0.48	0.37	0.50
School quality	31.9	35.1	33.1	35.3
Distance to jobs	40.3	45.5	40.1	42.4
Percent who move using the subsidy	0	0.55	0	0.47
Conditional on move using the subsidy				
Mean poverty rate	—	0.06	—	0.07
Mean percent white	—	0.69	—	0.75
School quality	—	38.2	—	38.9
Distance to jobs	—	48.3	—	43.7
Observations	165	204		

Sorting Models: Validation

- Fitted choice probabilities also replicate out-of-sample migration patterns and amenity exposures when households face different incentives and constraints!

	Section 8	
	Data	Model
Unconditional on move using the subsidy		
Mean poverty rate	0.27	0.25
Mean percent white	0.34	0.42
School quality	32.7	34.2
Distance to jobs	41.7	41.1
Percent who move/percent who move using the subsidy	0.63	0.70
Conditional on move using the subsidy		
Mean poverty rate	0.20	0.19
Mean percent white	0.38	0.50
School quality	33.6	35.2
Distance to jobs	42.4	41.0
Observations	172	

Sorting Model Extension: Dynamics



Econometrica, Vol. 84, No. 3 (May, 2016), 893–942

A DYNAMIC MODEL OF DEMAND FOR HOUSES AND NEIGHBORHOODS

BY PATRICK BAYER, ROBERT MCMILLAN, ALVIN MURPHY, AND CHRISTOPHER TIMMINS[1]

This paper develops a dynamic model of neighborhood choice along with a computationally light multi-step estimator. The proposed empirical framework captures observed and unobserved preference heterogeneity across households and locations in a flexible way. We estimate the model using a newly assembled data set that matches demographic information from mortgage applications to the universe of housing transactions in the San Francisco Bay Area from 1994 to 2004. The results provide the first estimates of the marginal willingness to pay for several non-marketed amenities—neighborhood air pollution, violent crime, and racial composition—in a dynamic framework. Comparing these estimates with those from a static version of the model highlights several important biases that arise when dynamic considerations are ignored.

KEYWORDS: Neighborhood choice, dynamic discrete choice, housing demand, hedonic valuation, amenities, unobserved heterogeneity, residential sorting.

1. INTRODUCTION

MODELS OF RESIDENTIAL SORTING AND HEDONIC EQUILIBRIUM PROVIDE the basis for several longstanding literatures in economics. A large body of theoretical research in public and urban economics, for example, has used these models to characterize the equilibrium structure of cities and the provision of public goods in a system of political jurisdictions.[2] Furthermore, empirical researchers have developed related estimable models in order to provide theoretically consistent estimates of household willingness to pay for a wide variety of non-marketed local goods (e.g., education, crime, and environmental amenities)[3] and as a tool for simulating how counterfactual policies would af-

[1]This paper is a revised version of NBER Working Paper 17250. We would like to thank Kelly Bishop, Morris Davis, Ed Glaeser, Phil Haile, Aviv Nevo, participants at the Econometric Society Summer Meetings, NBER Summer Institute, Regional Science Annual Meetings, Stanford Institute for Theoretical Economics, and seminar participants at the University of Arizona, Duke, UBC, Georgetown, Minnesota, NYU, Northwestern, Ohio State, Queen's, Rochester, St. Louis Federal Reserve, and Yale for many valuable suggestions. The co-editor and three anonymous referees provided numerous comments that have helped us improve the paper significantly. Thanks to Elliot Anenberg for excellent research assistance. Financial support from the National Science Foundation and SSHRC is gratefully acknowledged. All remaining errors are our own.

[2]Theoretical contributions to the residential sorting literature include papers by Ellickson (1971), Epple, Filimon, and Romer (1984), Epple and Romer (1991), Epple and Romano (1998), and Nechyba (1999, 2000). Related contributions to the literature analyzing hedonic equilibrium include Rosen (1974), Epple (1987), and Ekeland, Heckman, and Nesheim (2004).

[3]Empirical sorting papers include Epple and Sieg (1999), Bayer, Ferreira, and McMillan (2007), Ferreyra (2007), and Kuminoff (2012); for empirical analyses of hedonic equilibrium, see Bajari and Kahn (2005), Kuminoff and Jarrah (2010), and Bishop and Timmins (2011).

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- Bayer, McMillan, Murphy, and Timmins (ECMA 2016) extend Bayer et al. (2007) to add moving costs, forward-looking behavior, endogenous wealth, and type-specific preference heterogeneity
- Literature's methodological frontier
- Application to climate amenities and endogenous health (Mathes IER 2025)

Sorting Model Extension: Dynamics

- Each period, households maximize remaining lifetime utility:

Flow utility: $V_{i,j,t} = \alpha_h^{i,t} h_{j,t} + \alpha_g^{i,t} g_{j,t} + \alpha_p^{i,t} p_{j,t} + \lambda_{i,j,t} + \xi_{j,t} + \varepsilon_{j,t}^{i}$

Lifetime utility: $V_{i,j,t} + \beta E\left[\max_k \{V_{i,k,t+1}\}\right]$

- Solution depends on beliefs about future evolution of:
    - Amenities (e.g. air pollution, crime, neighborhood composition)
    - Housing prices (e.g. amenity capitalization)
    - Demographics (e.g. income, health)

- Identification and estimation details – see Bayer et al. (2016)

Sorting Model Extension: Dynamics

- Under a rational expectations assumption for beliefs, the size and direction of biases in WTP depends on how amenity levels are evolving

TABLE VI

WILLINGNESS TO PAY FOR A 10-PERCENT INCREASE IN AMENITIES—STATIC VERSUS DYNAMIC ESTIMATES BY INCOME

	Static			Dynamic		
	\$40,000	\$120,000	\$200,000	\$40,000	\$120,000	\$200,000
Percent white	1627.03	1901.43	2221.66	612.09	2428.93	4888.46
	(12.92)	(18.67)	(48.56)	(87.09)	(121.89)	(275.08)
Violent crime	−291.14	−380.66	−448.88	−350.18	−962.20	−1298.81
	(8.13)	(10.98)	(19.40)	(47.68)	(67.29)	(92.79)
Ozone	−66.24	−80.71	−97.04	−302.06	−380.03	−395.58
	(2.00)	(2.39)	(3.25)	(24.82)	(26.98)	(37.12)

Sorting Model Extension: Heterogeneous Beliefs

- **Hedonic and sorting models** following Tiebout (1956) and Rosen (1974) assume that buyers perceive product attributes identically *and* accurately.

- This assumption underlies our estimates of the WTP for environmental amenities

- **Some buyers and sellers are misinformed** (e.g. Pope JUE 2008, Pope LAND 2008, Ma IER 2019, Bakkensen and Barrage RevFinStud 2022, Fairweather et al. NBER 2024)

- Straightforward to fix measures of WTP for product attributes if we know (a) beliefs *and* (b) the parametric form of utility (Leggett ERE 2002)

Sorting Model Extension: Heterogeneous Beliefs

Environmental and Resource Economics **23:** 343–355, 2002.

Environmental Valuation with Imperfect Information

The Case of the Random Utility Model[1]

CHRISTOPHER G. LEGGETT
Industrial Economics, Incorporated 2067 Massachusetts Avenue Cambridge, MA 02140 (E-mail: cleggett@indecon.com)

Accepted 23 February 2002

Abstract. This paper considers welfare analysis with the random utility model (RUM) when perceptions of environmental quality differ from objective measures of environmental quality. Environmental quality is assumed to be an experience good, so that while perceptions of quality determine choices, *ex post* utility is determined by objective quality. Given this assumption, I derive a measure of the welfare impact of changes in environmental quality, and I show how this new welfare measure differs from the traditional welfare measure developed by Hanemann (1982). This new welfare measure provides an approach to measuring the value of information about environmental quality within the framework of the random utility model.

Key words: discrete choice, information, logit, perception, random utility model, welfare analysis

JEL classification: JEL Categories: Q26, D60, D80

1. Introduction

Consumers rarely have perfect information about the quality of the environmental goods that they purchase. Swimmers will commit to a lengthy drive to the beach with only limited knowledge about water quality, hunters will drive several hours to a hunting site after hearing rumors of plentiful game, and home buyers will purchase a house with no more than a rough idea about neighborhood air quality. In contrast, the quality of marketed goods is often easier to ascertain prior to purchase: tires are kicked, fruit is examined, and clothes are tried on.

Yet the standard practice for researchers using behavioral techniques to value changes in environmental quality is to assume that information is perfect and individuals' perceptions of quality are correct.[2] Because these perceptions – rather than objective, scientific measurements of quality – are what ultimately determine choices, standard welfare estimates derived from these choices will be incorrect when perceptions are wrong. This paper develops an approach to welfare analysis with the random utility model (RUM) when consumers' perceptions of quality are imperfect. A welfare measure is derived for situations where environmental quality

$$E[WTP] = \frac{1}{\alpha^i}\left[ln \sum_{C^1} exp\left(\hat{V}_{ij}^1\right) - ln \sum_{C^0} exp\left(\hat{V}_{ij}^0\right)\right]$$

Standard welfare measure in logit model

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Standard welfare measure in logit model, with adjustment for heterogeneous beliefs

$$= \frac{1}{\alpha^i}\left[\begin{array}{c} ln \sum_{C^1} exp\left(\hat{V}_{ij}^{1*}\right) - ln \sum_{C^0} exp\left(\hat{V}_{ij}^{0*}\right) \\ + \sum_{C^1}\left(\pi_{ij}^{1*}\left(\hat{V}_{ij}^{1} - \hat{V}_{ij}^{1*}\right)\right) - \sum_{C^0}\left(\pi_{ij}^{0*}\left(\hat{V}_{ij}^{0} - \hat{V}_{ij}^{0*}\right)\right) \end{array}\right]$$

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Industrial Economics, Incorporated 2067 Massachusetts Avenue Cambridge, MA 02140 (E-mail: cleggett@indecon.com)

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Abstract. This paper considers welfare analysis with the random utility model (RUM) when perceptions of environmental quality differ from objective measures of environmental quality. Environmental quality is assumed to be an experience good, so that while perceptions of quality determine choices, *ex post* utility is determined by objective quality. Given this assumption, I derive a measure of the welfare impact of changes in environmental quality, and I show how this new welfare measure differs from the traditional welfare measure developed by Hanemann (1982). This new welfare measure provides an approach to measuring the value of information about environmental quality within the framework of the random utility model.

Key words: discrete choice, information, logit, perception, random utility model, welfare analysis

JEL classification: JEL Categories: Q26, D60, D80

1. Introduction

Consumers rarely have perfect information about the quality of the environmental goods that they purchase. Swimmers will commit to a lengthy drive to the beach with only limited knowledge about water quality, hunters will drive several hours to a hunting site after hearing rumors of plentiful game, and home buyers will purchase a house with no more than a rough idea about neighborhood air quality. In contrast, the quality of marketed goods is often easier to ascertain prior to purchase: tires are kicked, fruit is examined, and clothes are tried on.

Yet the standard practice for researchers using behavioral techniques to value changes in environmental quality is to assume that information is perfect and individuals' perceptions of quality are correct.[2] Because these perceptions – rather than objective, scientific measurements of quality – are what ultimately determine choices, standard welfare estimates derived from these choices will be incorrect when perceptions are wrong. This paper develops an approach to welfare analysis with the random utility model (RUM) when consumers' perceptions of quality are imperfect. A welfare measure is derived for situations where environmental quality

$$= \frac{1}{\alpha^i}\left[\begin{array}{c} ln \sum_{C^1} exp\left(\hat{V}_{ij}^{1*}\right) - ln \sum_{C^0} exp\left(\hat{V}_{ij}^{0*}\right) \\ + \sum_{C^1}\left(\pi_{ij}^{1*}\left(\hat{V}_{ij}^{1} - \hat{V}_{ij}^{1*}\right)\right) - \sum_{C^0}\left(\pi_{ij}^{0*}\left(\hat{V}_{ij}^{0} - \hat{V}_{ij}^{0*}\right)\right) \end{array}\right]$$

choice probability

choice probability

Sorting Model Extension: Heterogeneous Beliefs

Environmental and Resource Economics **23:** 343–355, 2002. 343

Environmental Valuation with Imperfect Information

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<u>Note</u>: hedonic utility is the only welfare component not measured directly by the usual methods.

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<u>Measuring hedonic utility preferences</u>

- empirical information diffusion (Ma, 2019)
- survey (Bakkensen and Barrage, 2022)
- info treatment (Fairweather et al., 2024)

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Sorting Models: Summary

- Powerful microeconometric framework for identifying consumers' WTP for non-market attributes of differentiated goods
- Strategies for mitigating omitted variable bias are similar to hedonic models and also draw on techniques from the IO literature
- Well-identified models make accurate predictions for sorting behavior
- WTP can be useful for evaluating counterfactual policies
- Research frontiers include modeling dynamics and heterogeneity in beliefs

Outline

1. The hedonic property value model

2. Best practices for using price functions to estimate MWTP

3. Modeling sorting behavior

   - identification and estimation

   - validation

   - extensions: dynamics, heterogeneous beliefs

4. **Questions / Discussion**

Slides: https://nickkuminoff.github.io/webpage/hedonic.pdf