Connect-The-Dots: Identification of Heterogeneous Marginal Willingness to Pay Functions under Time-Varying Preferences

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Overview

What? How can we identify and estimate MWTP for neighborhood amenities when preferences are time-varying?

Why? Valuation of neighborhood amenities important for allocation of public funds and for measuring benefits of regulation and traditional methods assume non-timevarying preferences when identifying MWTP

How? Developing hedonic model for two-purchase individuals and applying it to valuation of changes in violent crime

Overview

The traditional approach and a few extensions

Alternative approach: Connect-The-Dots

Data

Results

Welfare analysis

Conclusion

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Previous literature

- Rosen (1974) sets the stage for the hedonic theory that connects residential choices and associated house prices to WTP for neighborhood amenities
- Rosen's 2nd step: $P_i^q = \frac{\partial P_i}{\partial q_i} = \gamma_0 + \gamma_1 q_i + \gamma_2 \underbrace{w_i}_{\text{i's charcteristics}} + \underbrace{\epsilon_i}_{\text{unobs. pref. shock}}$

  but well-known endogeneity problems due to sorting

▸ Rosen

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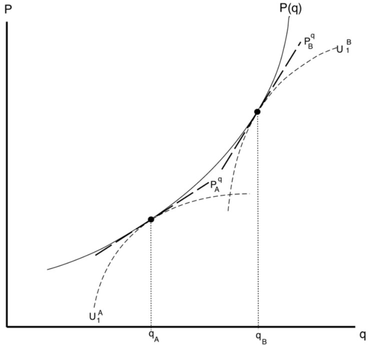

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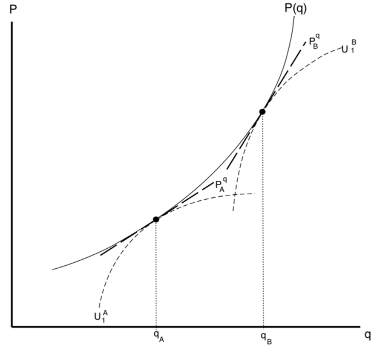

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Avoiding the endogenous preference shock

- Bajari & Benkard (2005): not estimating preferences in a traditional sense, but recovered at an individual level
- Preferences identified from conditions imposed by optimizing behaviour
- Individual heterogeneity embedded in parameters $\rightarrow$ no need for unobserved preference shock that caused endogeneity issues

▸ Bajari & Benkard

Solutions to Rosen's endogeneity problems using panel data

- Bishop & Timmins (2018) extend the approach to identify both individual-specific intercepts and slopes of MWTP using data on individuals who are observed in two purchase occasions
- Requires that both purchases lie on the same demand curve
- They assume preferences do not change over time to fulfill this ▸ extension
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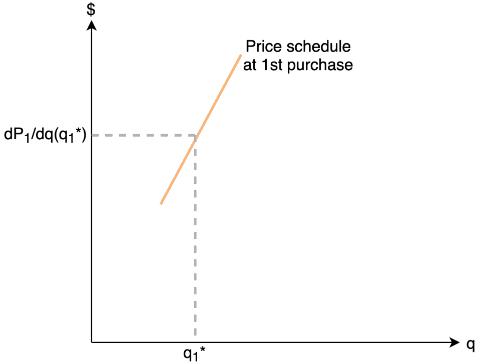

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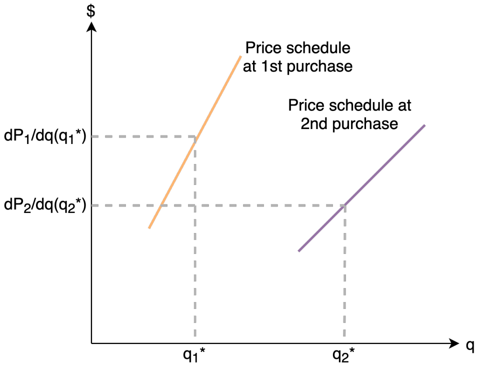

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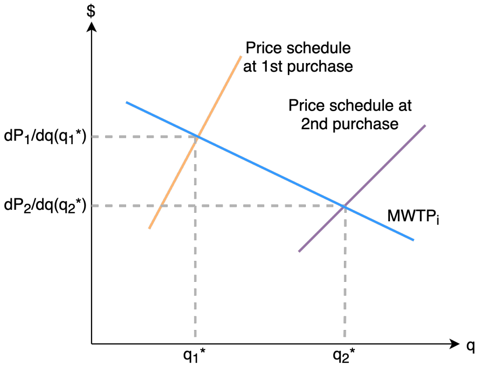

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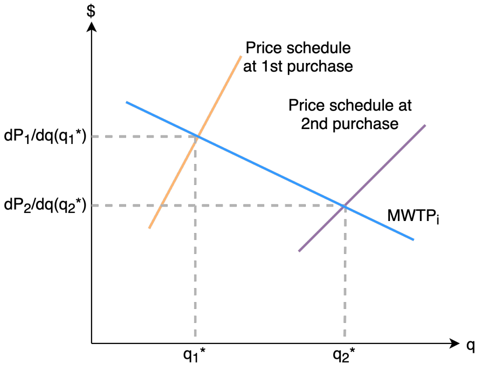

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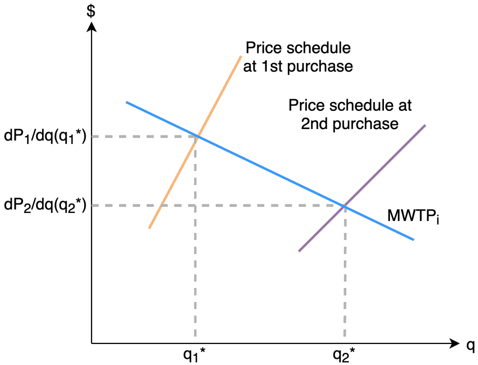

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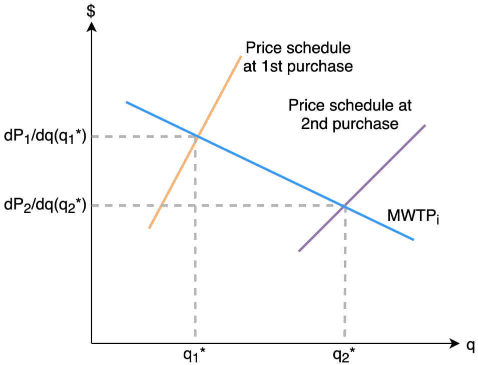

Overview

Estimation strategy

- Linear *individual-specific* MWTP for non-marginal changes in violent crime (q_{it})

$$MWTP_{q_{it}} = \mu_{i0} + \mu_{i1} q_{it} \tag{1}$$

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Step 1: Hedonic gradient

- Model does not rely on assumptions about shape of hedonic price
- Considered a function of amenity q_{it}, housing and neighborhood attributes, x_{it} through the unknown function $g(.)$:

$$P_{it} = g(q_{it}, x_{it}; \beta_t). \tag{2}$$

- The implicit price for the amenity is:

$$\frac{dP_{it}}{dq_{it}} \equiv P_{it}^{q} \tag{3}$$

Step 2a: Segmentation equations

- Sorting in equilibrium leads to a segmentation of the market described by the relationship between q and individual attributes (Mendelsohn (1985))
- Define the relationship between individual demographics w_{it} and violent crime q_{it} as

$$q_{it} = f(w_{it}; \alpha_i, \delta_t), \tag{4}$$

Step 2b: Adjustment

- Adjust characteristics at second purchase back to values at first purchase: $w_{i2} \rightarrow w_{i1}$
- Predict demand for violent crime at second purchase had her characteristics not changed:

$$\tilde{q}_{i2} = f(w_{i1}; \alpha_i, \hat{\delta}_2). \tag{5}$$

- Compute implicit price she would have had to pay for $\tilde{q}_{i2}$:
- Demand for first purchase is observed and implicit price is:

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- Demand for first purchase is observed and implicit price is:

$$\tilde{P}_{i1}^{q} = g'(q_{i1}, x_{i1}; \hat{\beta}_1). \tag{7}$$

Step 3: MWTP function inversion

- In equilibrium, implicit price equals MWTP $\rightarrow$ two equations with two unknowns (μ_{i0}, μ_{i1}):

$$\hat{P}^{q}_{i1} = \mu_{i0} + \mu_{i1} q_{i1} \tag{8}$$
$$\tilde{P}^{\tilde{q}}_{i2} = \mu_{i0} + \mu_{i1} \tilde{q}_{i2} \tag{9}$$

- Find the parameters of the MWTP function that "connect the dots" for each individual
- Identification requires variation in implicit prices and segmentation equations over time $\rightarrow$ panel data on home purchases, prices and buyers needed

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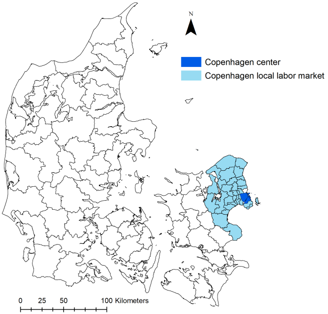
Data sources

- Danish register data on **demographics** of the **entire population** of individuals and households for the period 2008-2014
- **Sales prices** for the population of transacted houses and **housing characteristics** (location, size, rooms...) of all houses
- **Home ownership** that allows me to link demographic data to housing data via SSN and house id
- **Amenities**: number of victims of violent and property crime and school districts
    - Police reports with info on detailed type of crime, location and time of incidence
    - Violent crime: serious violent crime, rape, crime against life and body, murder, attempted murder, violence against public authorities (exclude: simple violence, threats, crime against personal freedom)
    - Property crime: thefts and robberies (exclude: blackmailing)

Data sample

- Restrict to parishes in Copenhagen local labor market 2008-2014 and exclude renters, private sales only
- Parishes: admin units that assign individuals to a local church. 2017 version: 294 parishes
- $\Rightarrow \sim 95,000$ buyers, $\sim 59,000$ housing transactions, $\sim 2,600$ repeat buyers ▸ Crime dist ▸ Sumstats

Figure 3: Copenhagen local labor market and average violent crime 2008-2014



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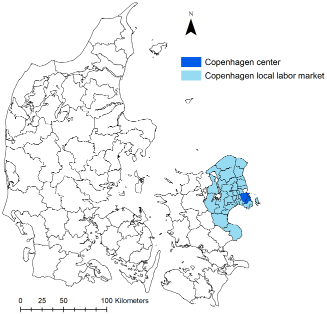

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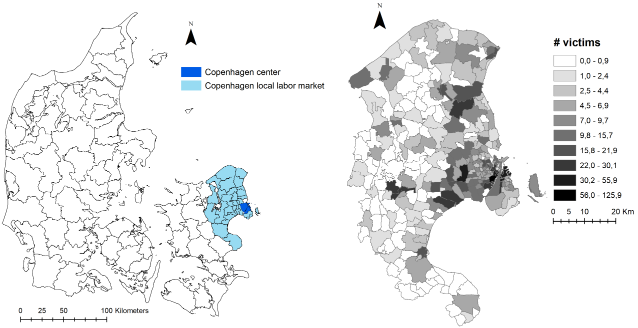

(a) Cph local labor market **(b)** # violent crime victims

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Empirical specification: Step 1 - Hedonic gradient

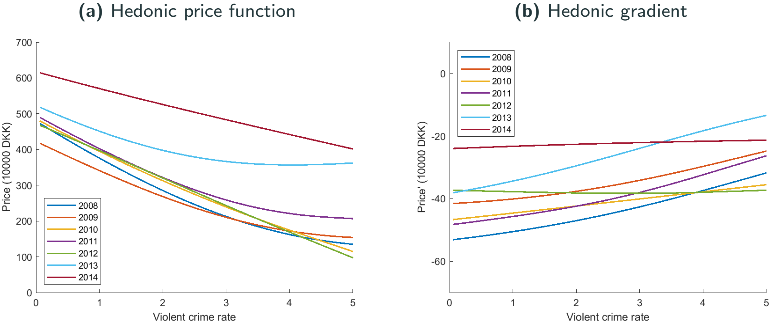
- Estimate gradient semi-parametrically using Robinson's method ▸ Details

$$P_{it}(q_{it}, x_{it}; \beta_t) = x_{it}'\beta_t^x + \Lambda(q_{it}; \beta_t) + \epsilon_{it}, \tag{10}$$

- q_{it}: violent crime pr. 1,000 inhabitants
- $\Lambda(.)$: flexible function of q_{it} (end up using local linear function w. bw $2.5 \cdot sd(q_{it})$, adaptive bw 0)
- ϵ_{it}: regression error
- x_{it}: vector of other housing or neighborhood attributes
    - quadratic functions of the property crime rate, square meters sold and number of rooms
    - dummy variables for bathroom, kitchen, apartment
    - school district fixed effects

Results: Step 1 - Hedonic gradient

Figure 4: Results of 1st Stage by Year, $P_t(q_{i,t})$



Note: The violent crime rate is measured as number of victims of violent crime per 1,000 people.

- Hedonic price function is positive and slopes downwards
- I.e. negative gradient (safety is a good) and shows variability over time

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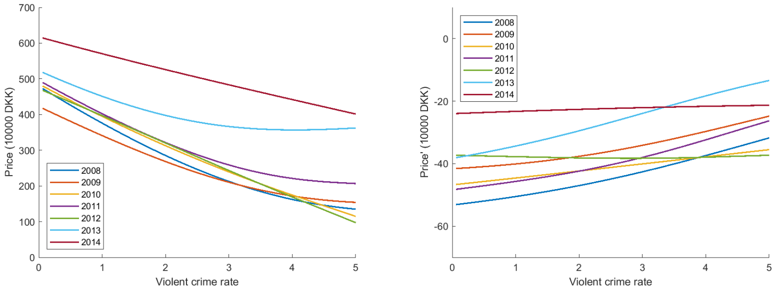

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- Hedonic price function is positive and slopes downwards
- I.e. negative gradient (safety is a good) and shows variability over time
- But gradients slope upwards as usually found in the literature.
- This is the simple measure of WTP often found in the literature (high crime areas: lower WTP for reductions)

Results: Step 2 - Segmentation

Table 1: Segmentation equation for violent crime rate

	(1)	(2)	(3)	(4)	(5)
Year	-0.043***	-17.737	-0.040***	-0.041***	
	(0.01)	(23.10)	(0.01)	(0.01)	
Year^2		0.004			
		(0.01)			
Number of children (ref. 0)					
1 child	-0.352***	-0.350***	-0.336***	-0.351***	-0.348***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
2 children	-0.388***	-0.387***	-0.366***	-0.393***	-0.385***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
3+ children	-0.448***	-0.447***	-0.420***	-0.454***	-0.452***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Household income (10,000 DKK)			-0.001		
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Household income (10,000 DKK)^2			0.000		
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$\mathbb{I}[\textit{Divorce}]$				0.085	
					(0.07)
Constant	87.162***	17,880.2	82.509***	83.524***	1.313***
	(18.83)	(23228.41)	(18.68)	(18.92)	(0.05)
N	6,167	6,167	6,167	6,167	6,167
Year FE	*No*	*No*	*No*	*No*	*Yes*
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Results: Step 2 - Segmentation

Table 1: Segmentation equation for violent crime rate

	(1)	(2)	(3)	(4)	(5)
Year	-0.043***	-17.737	-0.040***	-0.041***	
	(0.01)	(23.10)	(0.01)	(0.01)	
Year^2		0.004			
		(0.01)			
Number of children (ref. 0)					
1 child	-0.352***	-0.350***	-0.336***	-0.351***	-0.348***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
2 children	-0.388***	-0.387***	-0.366***	-0.393***	-0.385***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
3+ children	-0.448***	-0.447***	-0.420***	-0.454***	-0.452***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Household income (10,000 DKK)			-0.001		
			(0.00)		
Household income (10,000 DKK)^2			0.000		
			(0.00)		
$\mathbb{I}[Divorce]$				0.085	
					(0.07)
Constant	87.162***	17,880.2	82.509***	83.524***	1.313***
	(18.83)	(23228.41)	(18.68)	(18.92)	(0.05)
N	6,167	6,167	6,167	6,167	6,167
Year FE	*No*	*No*	*No*	*No*	*Yes*
Individual FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

- Consumption of violent crime tends to drop over time and with children

Results: Step 2 - Segmentation

- Children have an economically significant effect on demand
  - 2008, 0 children: demand is 0.818
  - 2008, 1 child: demand is 0.818 - 0.352
- Income, debt, assets, divorce don't have any significant effects once controlling for individual FE
- Individual FE account for a significant share of the variation

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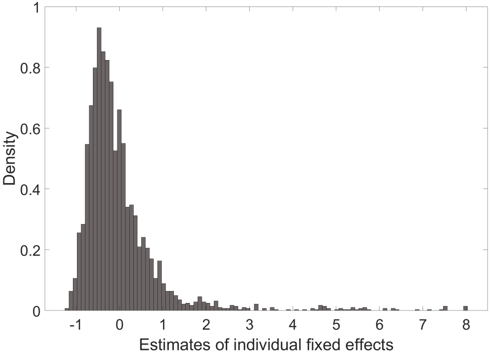
Figure 5: Distribution of fixed effects in demand for violent crime



Results: Step 3 - Inversion

- With demand estimated for the 2nd purchase, the implicit price is found by using nearest neighbor interpolation of the gradient function in that year
- $\rightarrow$ two points on the same demand curve

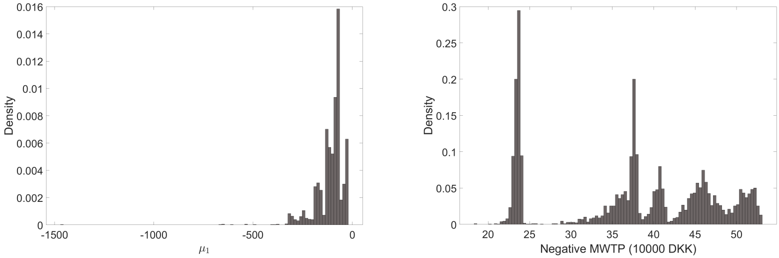
$$\hat{\mu}_{i1} = \frac{\tilde{P}_{i2}^{\tilde{q}} - \hat{P}_{i1}^{q}}{\tilde{q}_{i2} - q_{i1}} \tag{11}$$

$$\hat{\mu}_{i0} = \hat{P}_{i1}^{q} - \hat{\mu}_{i1} q_{i1} \tag{12}$$

Summary of results

Figure 6: CTD: Distribution of $\hat{\mu}_1$ and negative MWTP

(a) μ_1 **(b)** -MWTP for violent crime



Note: Removing individuals with the 5% most extreme estimates of MWTP. Violent crime measured as number of victims of violent crime per 1,000 people.

- $\hat{\mu}_1 < 0$ as expected
- $-MWTP > 0$ and in the range 200,000-550,000 DKK ($\approx$ 30,000 - 80,000 USD)
- Peaks in MWTP distribution reflect heterogeneity from children and time

▸ Estimats of μ_0

Results using Rosen

- Get hedonic gradient for each individual at observed crime levels using interpolation
- Regress hedonic gradient on individual attributes, fixed effects and crime
- positive slope: individauls w. high q have lower MWTP for reductions $\rightarrow$ biased Rosen 2nd stage

▸ Rosen 2nd stage

Overview

Welfare analysis

- WTP to avoid a 30% increase in violent crime using CTD vs Rosen's approach ▸ Details
- Generally find that MWTP is increasing in violent crime using CTD
- Rosen: suffers from a bias implying decreasing MWTP as crime increases (demand for safety is upward-sloping)
- Rosen: overstates the WTP for a reduction in crime and understates the WTP to avoid an increase in crime

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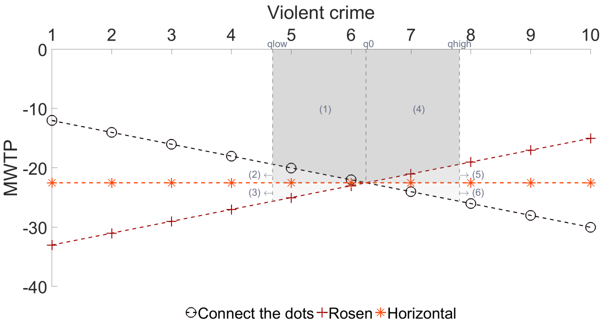
Figure 7: Example: computing WTP using different methods



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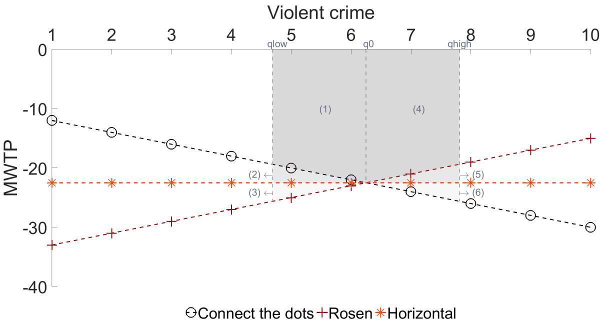

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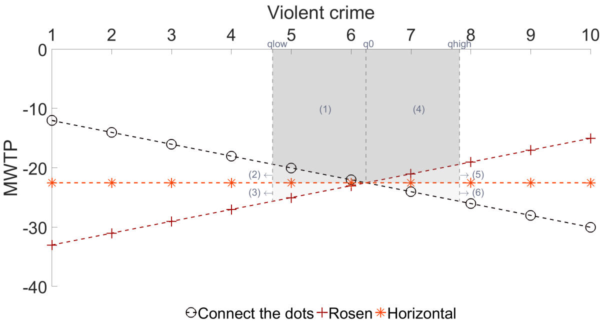

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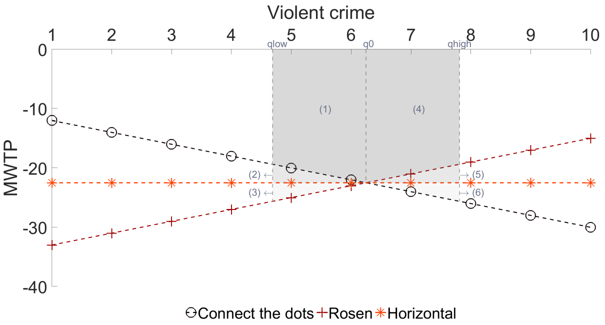
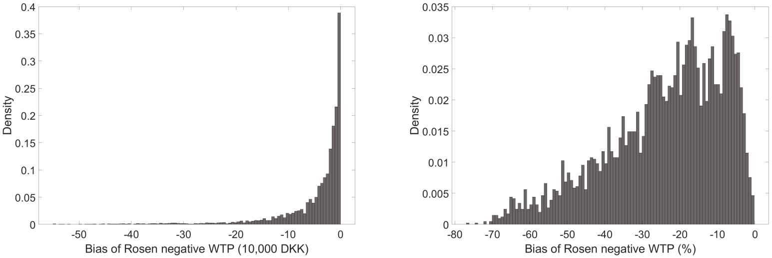


Welfare analysis: Rosen's bias

- Significant (Epple-style) bias in WTP when using Rosen's method despite taking individual heterogeneity into account
- Bias in the range 0 to -100,000 DKK (≈0 to -15,000 USD)
- Understatement of the cost of crime of up to -70% (-24.4% on average)

Figure 8: Bias of Rosen's negative WTP for a 30% increase in violent crime

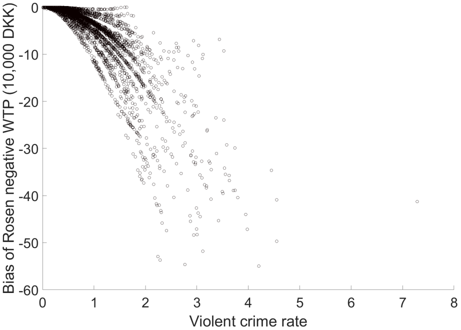
(a) 10,000 DKK **(b)** % difference



Note: The violent crime rate is measured as number of victims of violent crime per 1,000 people.

Welfare analysis: Rosen's bias by crime level

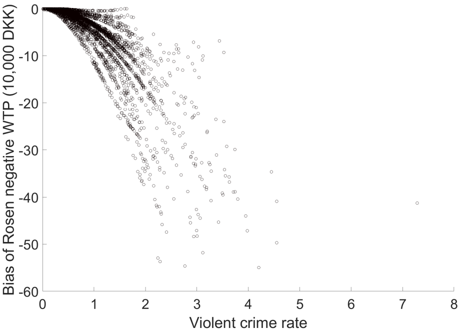
Figure 9: Bias of Rosen's negative WTP for a 30% increase in violent crime



Welfare analysis: Rosen's bias by crime level

- Bias in cost of crime even larger for households living in high-crime areas

Figure 9: Bias of Rosen's negative WTP for a 30% increase in violent crime



Welfare analysis: Rosen's bias by crime level

- Bias in cost of crime even larger for households living in high-crime areas
- In most crime-intensive areas, bias is up to -500,000 DKK (-72,000 USD)

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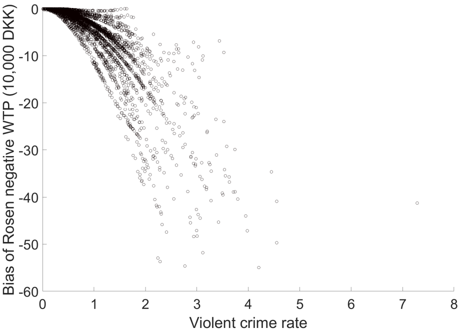

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- In most crime-intensive areas, bias is up to -500,000 DKK (-72,000 USD)
- $\rightarrow$ concern from policy-perspective: Rosen's method understates the costs of crime increases *more* in high-crime areas (where reductions needed) than in safer areas

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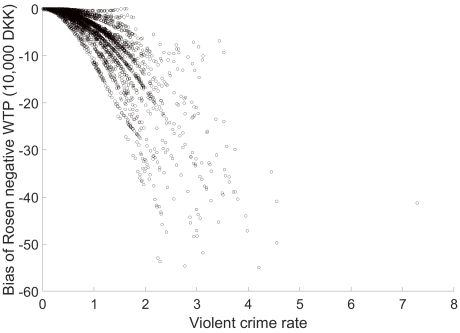

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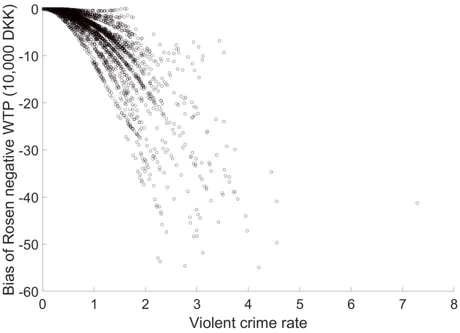
- $\rightarrow$ concern from policy-perspective: Rosen's method understates the costs of crime increases *more* in high-crime areas (where reductions needed) than in safer areas
- $\rightarrow$ if not accounting for this bias, welfare-burden of the bias would fall more heavily on high-crime areas (often disadvantaged households)

Figure 9: Bias of Rosen's negative WTP for a 30% increase in violent crime



Overview

The traditional approach and a few extensions

Alternative approach: Connect-The-Dots

Data

Results

Welfare analysis

Conclusion

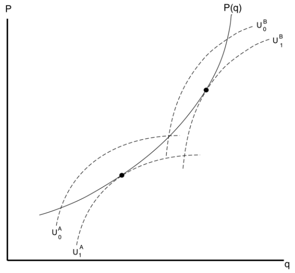
Conclusions

- Traditional hedonic methods only provide valid approximations of the WTP for *marginal* changes in (dis)amenities. Most policy-relevant changes tend to be non-marginal
- Accurately recovering the entire MWTP *function* is therefore important, but the literature has struggled with how to do this
- I develop a method that identifies both heterogeneous intercepts and slopes of individual MWTP functions while allowing for time-varying preferences
- I compare estimated WTP for large increases in violent crime to estimates using the traditional approach from Rosen (1974)
- I find that the traditional method severely understates the costs of 30% increases in crime by up to 70% and 24.4% on average
- This understatement is worse in high-crime areas
- Policy-makers should account for this bias and the heterogeneity in WTP when designing optimal policies

Overview

- The slope of the indifference curve in (q, P) space reflects the willingness to give up an additional unit of other consumption in exchange for more q
- That point on the slope of the hedonic price function reveals the otherwise unobserved slope of their indifference curve
- Estimate MWTP function in 2nd step as a function of $q \rightarrow$ measure value of non-marginal change in q:

Figure 10: Picking q to optimize utility



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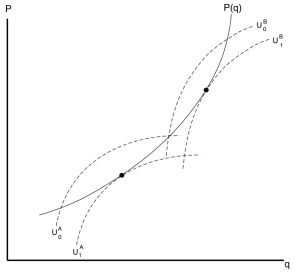

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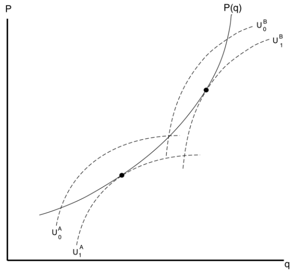

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$$P_i^q = \frac{\partial P_i}{\partial q_i} = \gamma_0 + \gamma_1 q_i + \gamma_2 \underbrace{w_i}_{\text{i's charcteristics}} + \underbrace{\epsilon_i}_{\text{unobs. pref. shock}}$$

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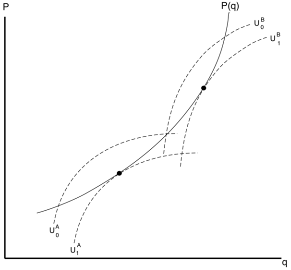


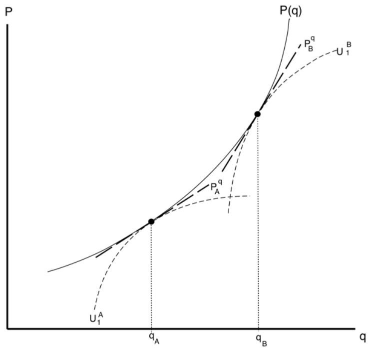
Problems with Rosen's approach

- When individuals sort along the hedonic price function $P(q)$, they both choose the level of q and the implicit price P_i^q
- Non-linear hedonic price: high unobserved preferences ϵ_i for $q \rightarrow$ high value of q and a high implicit price (if $P(q)$ is convex)
- $\rightarrow \epsilon_i$ is correlated with q_i and P_i^q

Back

Problems with Rosen's approach

Figure 11: Picking q to optimize utility with non-linear hedonic price



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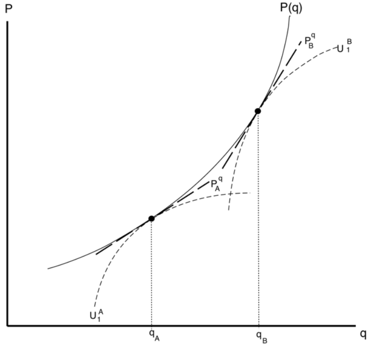

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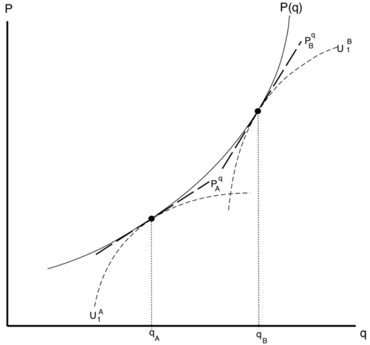

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Solutions to Rosen's endogeneity problems

- Bajari & Benkard (2005) invented an approach where preferences are not estimated in a traditional sense, but recovered at an individual level
- Individual preference parameters are identified from the conditions imposed by optimizing behaviour

$$\max_{q,x,c} U(q,x;\kappa) = \kappa_{1,i}q + \kappa_{2,i}x + c, \; s.t. \; c + P(q,x) = I \tag{13}$$

- Solve for indirect utility V and solve FOC wrt. (q,x)

$$\frac{\partial V_i}{\partial q} : \underbrace{\kappa_{1,i}}_{MWTP} = \underbrace{\frac{\partial P}{\partial q}}_{observed} \tag{14}$$

- Individual heterogeneity is embedded in parameters. This avoids the need for an unobserved preference shock that caused endogeneity issues
- But rely on functional form assumptions to identify MWTP *function* from just one observation of (P,q)

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Problems with Bishop and Timmins (2018)

- Identifying coefficients on time-varying preference shifters requires additional repeat sales (3 sales for 1 parameter)
- Vicious circle
    - More transactions needed to identify effects of time-varying preference shifters
    - $\rightarrow$ time dimension of the panel increases
    - $\rightarrow$ the number of other time-varying attributes that might change increases
    - $\rightarrow$ ignore the effects of time-varying preference shifters and assume preferences are nevertheless unchanged between purchase occasions

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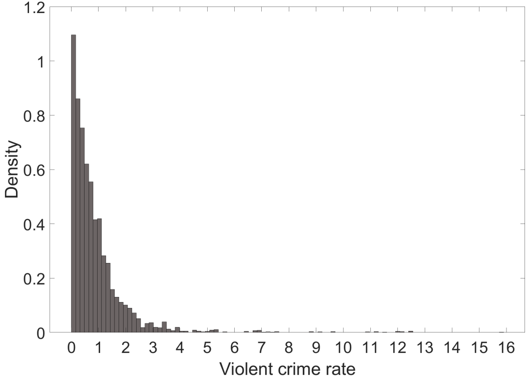
Distribution of violent crime

Figure 12: Probability density function of number of victims of violent crime per 1,000 people



Note: Violent crime rate is defined as the number of victims of violent crime per 1,000 people.

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Summary stats (properties)

Table 2: Summary statistics of property transactions

	Mean	S.d	Median	N
Violent crime	10.18	16.51	6.00	58,920
Property crime	150.28	503.49	49.00	58,920
# sqm sold	475.51	453.00	347.00	58,920
$\mathbb{I}$[apartment]	0.37	0.48	0.00	58,920
$\mathbb{I}$[bath]	0.99	0.09	1.00	58,920
$\mathbb{I}$[preserved]	0.02	0.13	0.00	58,920
Build year	1956	33.02	1963	58,542
# rooms	4.02	1.39	4.00	58,920
Km to Copenhagen center	17.23	13.47	12.61	58,920
Inhabs. pr. km^2	3,748	5,456	1,720	58,920

Sample criteria: Only using one property observation within the household in the year. *Note:* $\mathbb{I}$ is the indicator function.

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Summary stats (buyers)

Table 3: Summary statistics of buyers at time of purchase by total number of purchases

	Mean	S.d	N
1 purchase			
Age	38.85	11.94	92,121
$\mathbb{I}$[couple]	0.83	0.38	92,121
$\mathbb{I}$[male]	0.50	0.50	92,121
$\mathbb{I}$[has children]	0.56	0.50	92,121
$\mathbb{I}$[has school age child]	0.23	0.42	92,121
Education			
Unskilled	0.04	0.18	92,121
High school	0.17	0.38	92,121
Vocational/Short Cycle Tertiary	0.25	0.43	92,121
Medium Cycle Tertiary	0.29	0.45	92,121
$\mathbb{I}$[divorce]	0.03	0.17	76,408
Household total inc. (10t DKK)	76.03	27.44	83,036
Household assets (10t DKK)	272.48	113.21	82,916
Household debt (10t DKK)	248.18	159.49	92,101
$\mathbb{I}$[new job municipality]	0.37	0.48	92,121
$\mathbb{I}$[live in big city]	0.54	0.50	92,121

Note: $\mathbb{I}$ is the indicator function. $\mathbb{I}$[new job municipality]$= 1$ if either or both of the household members gets a job in t in another municipality than where they had a job in $t-1$. Monetary terms deflated by 2011 consumer price index.

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Summary stats (buyers)

Table 4: Summary statistics of buyers at time of purchase by total number of purchases

	Mean	S.d	N
2 purchases, 1st purchase			
Age	34.70	9.99	2,670
$\mathbb{I}$[couple]	0.77	0.42	2,670
$\mathbb{I}$[male]	0.51	0.50	2,670
$\mathbb{I}$[has children]	0.45	0.50	2,670
$\mathbb{I}$[has school age child]	0.16	0.36	2,670
Education			
Unskilled	0.03	0.17	2,670
High school	0.21	0.41	2,670
Vocational/Short Cycle Tertiary Tertiary	0.23	0.42	2,670
Medium Cycle Tertiary	0.28	0.45	2,670
Long Cycle Tertiary	0.24	0.43	2,670
Household total inc. (10t DKK)	71.45	26.83	2,438
Household assets (10t DKK)	267.42	113.41	2,375
Household debt (10t DKK)	242.71	202.40	2,670
$\mathbb{I}$[new job municipality]	0.42	0.49	2,670
$\mathbb{I}$[live in big city]	0.69	0.46	2,670

Note: $\mathbb{I}$ is the indicator function. $\mathbb{I}$[new job municipality]$= 1$ if either or both of the household members gets a job in t in another municipality than where they had a job in $t-1$. Monetary terms deflated by 2011 consumer price index.

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Summary stats (buyers)

Table 5: Summary statistics of buyers at time of purchase by total number of purchases

	Mean	S.d	N
2 purchases, 2nd purchase			
Age	38.07	9.73	2,670
$\mathbb{I}$[couple]	0.80	0.40	2,670
$\mathbb{I}$[male]	0.51	0.50	2,670
$\mathbb{I}$[has children]	0.65	0.48	2,670
$\mathbb{I}$[has school age child]	0.23	0.42	2,670
Education			
Unskilled	0.02	0.15	2,670
High school	0.13	0.34	2,670
Vocational/Short Cycle Tertiary	0.25	0.43	2,670
Medium Cycle Tertiary	0.29	0.45	2,670
Long Cycle Tertiary	0.30	0.46	2,670
Household total inc. (10t DKK)	79.19	28.71	2,447
Household assets (10t DKK)	282.13	114.90	2,461
Household debt (10t DKK)	283.56	163.53	2,670
$\mathbb{I}$[new job municipality]	0.34	0.47	2,670
$\mathbb{I}$[live in big city]	0.54	0.50	2,670

Note: $\mathbb{I}$ is the indicator function. $\mathbb{I}$[new job municipality]$= 1$ if either or both of the household members gets a job in t in another municipality than where they had a job in $t-1$. Monetary terms deflated by 2011 consumer price index.

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Additional summary stats

- Parishes per school district: mean 2, median 4, max. 14
- School district size (km^2): mean 26 , median 20 , max. 122 , min. 1
- Parish size (km^2): mean 9.7, median 7.0, max 49.3, min. 0.1

Robinson 2-step estimation

For each year:

1. Estimate $\mathbb{E}[a_{it}|q_{it}], a_{it} \in \{x_{it}, p_{it}\}$ using non-parametric regression of x_{it} controls and price p_{it} on q_{it}. Compute predicted value and then residuals.
2. OLS of residualized p_{it} on residualized x_{it} from 1) (consistent estimates of effect of x_{it} on p_{it}, β_t^x). Compute predicted value and subtract from observed p_{it} to get residual.
3. Non-parametric regression of residualized p_{it} from 2) on q_{it}.
4. For plotting hedonic price, use (10) evaluated for each data point q_{it} and level shifted with predicted mean of $x_{it}'\beta_t^x$ (i.e. using predicted value from 1) at each data point for q_{it})

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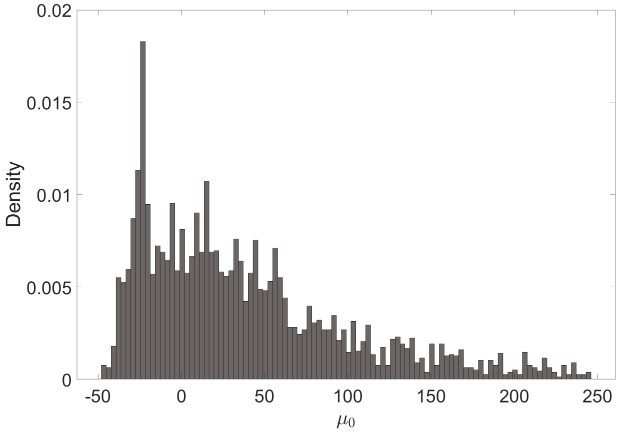
Distribution estimates of mu_0

Figure 13: CTD: Results of Inversion for μ_0

(a) μ_0



Note: Removing individuals with the 5% most extreme estimates of MWTP. Violent crime measured as number of victims of violent crime per 1,000 people.

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Results: Rosen 2nd stage

Table 6: Rosen 2nd stage: OLS of MWTP with individual fixed effects

	(1)	(2)	(3)	(4)
Violent crime rate	1.671***	2.174***	1.854***	2.103***
	(0.13)	(0.18)	(0.12)	(0.19)
Number of children (ref. 0)				
1 child	-0.848**			-0.892***
	(0.34)			(0.34)
2 children	-0.744**			-0.662*
	(0.37)			(0.37)
3+ children	-1.956***			-1.929***
	(0.62)			(0.62)
1 child × Violent crime rate	0.516*			0.583*
	(0.31)			(0.31)
2 children × Violent crime rate	0.543**			0.598**
	(0.27)			(0.27)
3+ children × Violent crime rate	0.664			0.896*
	(0.53)			(0.53)
Year	3.754***	3.740***	3.694***	3.742***
	(0.03)	(0.03)	(0.03)	(0.04)
Household income (10,000 DKK)		-0.001		0.000
		(0.00)		(0.00)
Violent crime rate × Household income (10,000 DKK)		-0.004**		-0.005**
		(0.00)		(0.00)
$\mathbb{I}[divorce]$			-1.374***	-1.308***
			(0.43)	(0.44)
$\mathbb{I}[divorce]$ × Violent crime rate			-0.111	-0.160
			(0.33)	(0.34)
Constant	- 7,589.319***	- 7,561.693***	- 7,469.329***	- 7,564.777***
	(69.18)	(61.84)	(60.39)	(70.41)
N	6,167	6,167	6,167	6,167

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Computing WTP of redcution from q_0 to q_{low}

- MWTP using CTD:

$$MWTP_{it}^{CTD} = \mu_{i0} + \mu_{i1} q_{it} \tag{15}$$

- WTP to avoid an increase in violent crime for i is then calculated for each individual by

$$\begin{aligned} WTP_{it}^{CTD} &= -\int_{q_{high}}^{q_0} (\mu_{i0} + \mu_{i1} q) dq \\ &= -(\mu_{i0} \cdot (q_{it,high} - q_{it,0}) + 0.5 \cdot \mu_{i1}(q_{it,high}^2 - q_{it,0}^2)). \end{aligned} \tag{16}$$

- MWTP using Rosen:

$$MWTP_{it}^{R} = \alpha_0 + \alpha_1 \cdot q_{it} + \epsilon_{it}, \tag{17}$$

- WTP using Rosen:

$$WTP_{it}^{R} = -(\alpha_0 \cdot (q_{it,high} - q_{it,0}) + 0.5 \cdot \alpha_1(q_{it,high}^2 - q_{it,0}^2)). \tag{18}$$

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