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Is Tourism good for Locals? Evidence from Barcelona

Treb Allen[1] Simon Fuchs[3] Sharat Ganapati[4]
Alberto Graziano[2] Rocio Madera[5] Judit Montoriol-Garriga[2]

[1]Dartmouth College

[2]CaixaBank Research

[3]FRB Atlanta

[4]Georgetown University

[5]Southern Methodist University

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Tourism is important

- Big part of the economy
  - 7% of global exports
  - In Spain: Tourism amounts to 50% of total goods exports
- Growing part of the economy
  - 50% increase in past 10 years
  - In Spain: Second fasted growing sector
- If tourism improves terms of trade for locals, should be welfare improving

Local Backlash against Tourism

This Paper: Three Contributions

1. **(Big) Data** on spatial expenditures
   - 500M transactions across 1,000 census blocks (origin-destination-product-month)
2. **Specific factor trade model** in a rich urban geography
   - Complex spatial patterns of consumption and production
   - Intuitive analytical expression enabling intra-city welfare analysis
3. **"Hybrid" empirical approach** marrying applied & general equilibrium tools
   - Use GE theory to design non-parametric regressions
   - Use plausibly exogenous variation in tourist composition to estimate them

Literature

Urban Quantitative Spatial Economics

- Ahlfeldt et al. (2015), Monte et al. (2018), Allen and Arkolakis (2016)

Big Data Spatial Economics

- Athey et al. (2018), Athey et al. (2020), Couture (2016), Couture et al. (2020), Davis et al. (2019), Agarwal et al. (2017), Carvalho et al. (2020)

Impact of Tourism

- Almagro and Domínguez-Iino (2019), García-López et al. (2019), Faber and Gaubert (2019)

Ricardo-Viner trade models

- Mussa (1974), Mussa (1982), Jones (1975),Kovak (2013), Dix-Carneiro and Kovak (2017)

Outline

1. Data & Stylized Facts
2. Theory
3. Empirics & Welfare effects

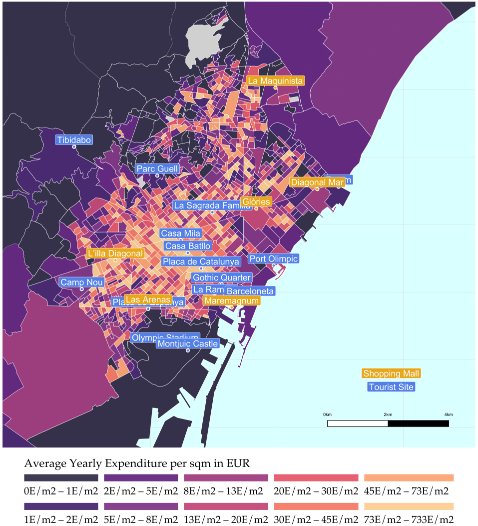
Data & Stylized Facts

A new Spatial Dataset for Barcelona

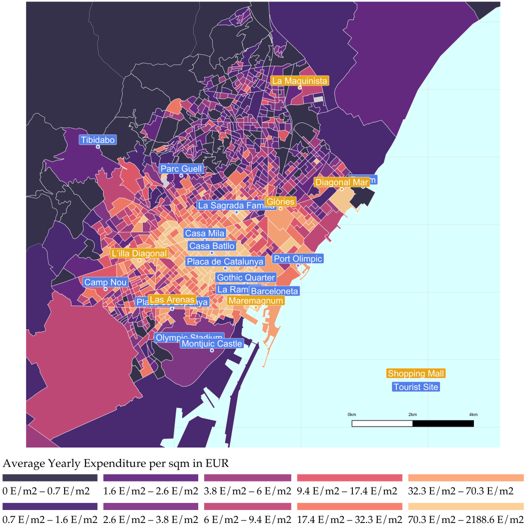
- Electronic transaction data from Caixa Bank (CXBK)
  - Account data for customers + point-of-sale data
  - Annually: 165+M transactions, 3B euros of value
  - 50% of all electronic transactions, 3% of all GDP
  - January 2017 - December 2019
- Our data aggregates to:
  - Locals: 1095 residential tiles x 1095 consumption tiles x 20 sectors x 36 months
  - Tourists: country of origin x 1095 consumption tiles x 20 sectors x 36 months
- Other data:
  - Commuting data (from mobile phone locations)
  - Housing prices (from "Spanish Zillow") Additional Data

Fact 1: Tourist and Local consumption geographies differ

Local Expenditures in Barcelona

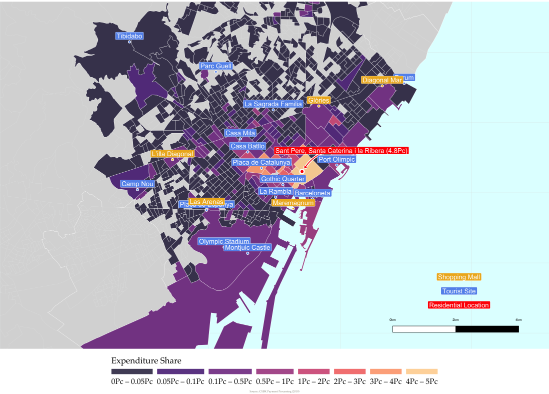


Tourist Expenditures in Barcelona

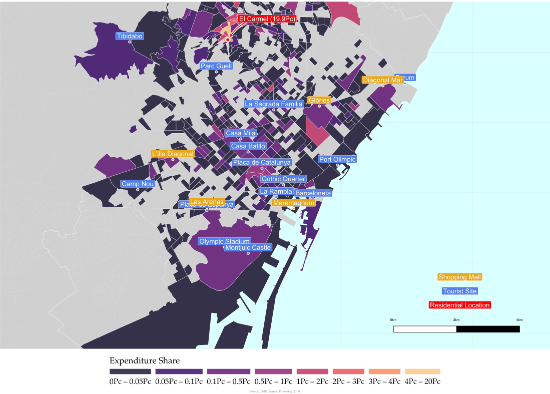


Fact 2: Local's consumption geographies differ by residence

Spatial Expenditure Shares for a Resident of Sant Pere, Santa Caterina i la Ribera



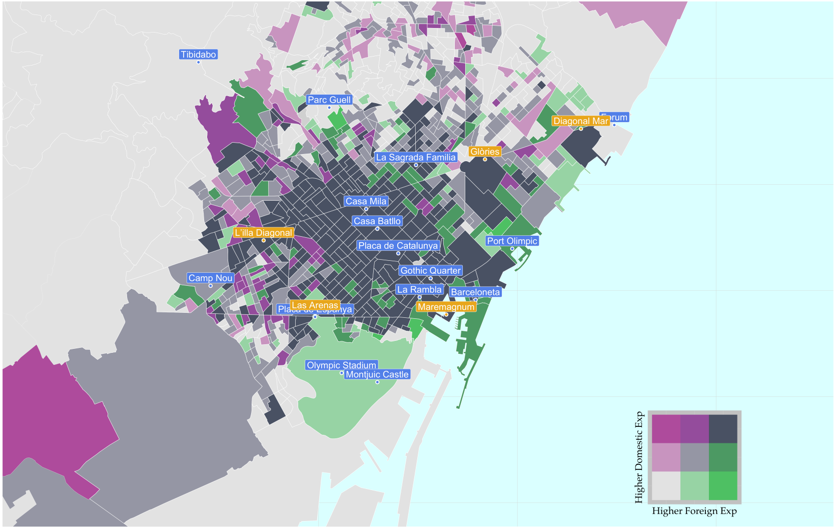
Spatial Expenditure Shares for a Resident of El Carmel



Sectoral Gravity Results

Fact 3: Tourist's consumption geographies differ by their origin

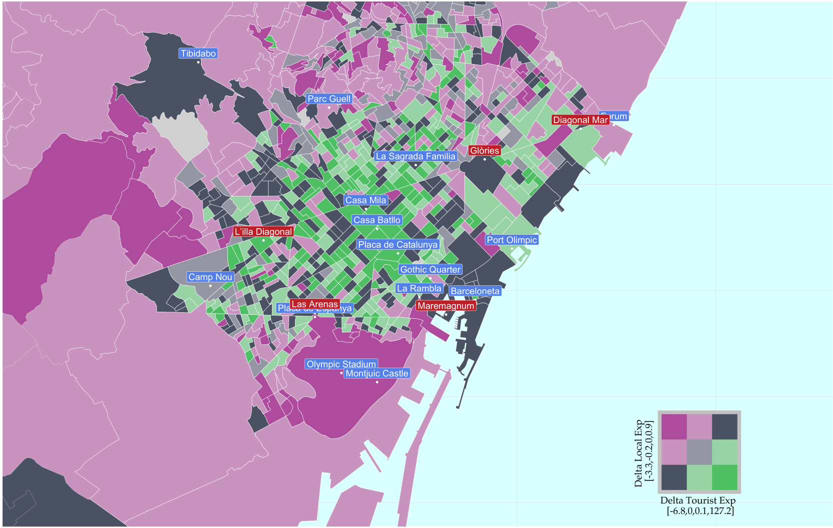
Spanish Tourists vs Foreign Tourist Expenditures



Source: CXBK Payment Processing (2019)

Fact 4: Tourist consumption crowds out local consumption

Change Tourist and Local Expenditure (August vs February 2019, Euro/m2)



Source: CXBK Payment Processing (2019)

Theory

A Specific factors trade model with rich urban geography

- Specific factors
  - Production requires local labor and a (externally owned) specific factor.
- Trade Model
  - Numeraire sector $s = 0$ costlessly traded.
  - Sectors $s \in 1, ..., S$ consumed by locals and tourists.
  - Total tourism expenditure exogenously given (tourist "shock").
- Rich urban geography
  - N locations. A good is a sector x location.
  - A local residing in block n chooses what goods to consume, produce.

Intuitive analytical expression for intra-city welfare analysis

Theorem (Welfare Effect)

Consider a representative local with homothetic preferences residing in block n. Applying envelope theorem to consumption, production optimization problems yields:

$$d \ln u_n = \sum_i \sigma_{ni} \partial \ln w_{is} - \sum_{i,s} \pi_{nis} \partial \ln p_{is}.$$

- Estimating the welfare effects of tourism requires:
  - Commuting data $\{\sigma_{ni}\}_{n=1,i=1}^{N,N}$
  - Spatial Expenditure data $\{\pi_{ni,s}\}_{n=1,i=1,s=0}^{N,N,S}$
  - Estimates of key elasticities: $\left\{\frac{\partial \ln p_{is}}{\partial \ln E_i^T}, \frac{\partial \ln w_i}{\partial \ln E_i^T}\right\}_{i=1,s=0}^{N,S}$

Theory Details

Empirics & Welfare effects

Empirics

1. A “deductive” approach: Simple regressions
   - Advantage: Atheoretical
   - Disadvantage: Average treatment effects only
2. An “inductive” approach: Theoretical predictions
   - Advantage: Heterogeneous treatment effects for welfare
   - Disadvantage: Additional assumptions (e.g. market clearing, functional form)
3. Hybrid Approach: Theory predicts the welfare effects, data validates.

Empirics

1. **Deductive Approach**

2. Inductive Approach

3. Hybrid Approach

Deductive Approach

- Deductive Approach: Recover average treatment effects from regressions

$$\Delta \ln p_{ismt} = \gamma_{is} + \gamma_{ts} + \beta_s^p \times \Delta \log E_{itm}^T + \epsilon_{ismt}, \quad (1)$$

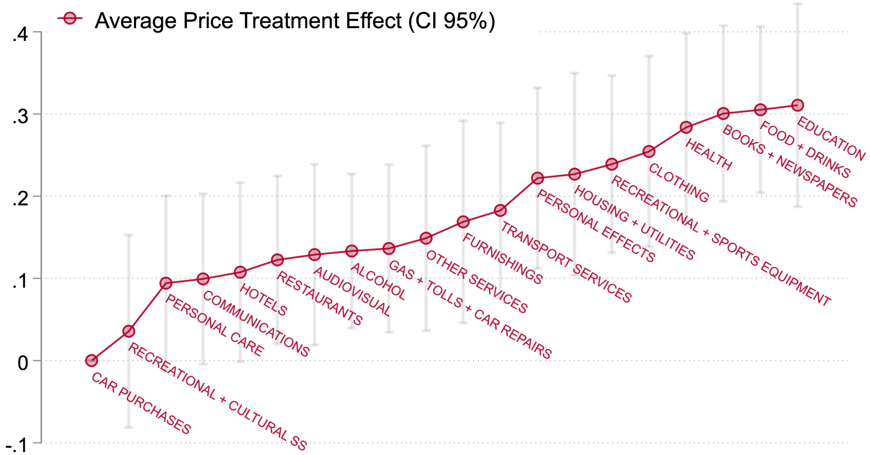
$$\Delta \ln w_{imt} = \gamma_{it} + \gamma_{im} + \gamma_{tm} + \beta^w \times \Delta \log E_{itm}^T + \epsilon_{imt}, \quad (2)$$

  - Recover prices from gravity fixed effects, i.e. $\Delta \ln p_{ismt} = \frac{1}{1-\sigma_s} \Delta \ln \delta_{istm}$
  - Recover wages from gravity commuting model, i.e. $w_{imt} = \sum_{n=1}^{N} \left(\frac{L_{ni}}{R_n}\right) v_{nmt}$

- Bartik decomposes expenditures into group composition and seasonal demand

Bartik Detail First Stage

Average Price effects by Sector



Is tourism good for the locals (on average)?

- Can aggregate to welfare using a simplified version of welfare results

$$\frac{d \ln u_n}{\partial \ln E^T} = \frac{\partial \ln \bar{w}}{\partial \ln E_i^T} - \sum_s \pi_{ns} \frac{\partial \ln \bar{p}_s}{\partial \ln E_i^T}$$

- Results
  - Price Index elasticity: -.23
  - Wage elasticity: .05 Income Regression
  - Welfare elasticity: -.18
  - Average increase between February and July $\approx$ 70.3pc
  - Implies net welfare deterioration 12.67pc

Empirics

1. Deductive Approach
2. **Inductive Approach**
3. Hybrid Approach

Analytical Expression for Price and Wage effects

- Impose market clearing conditions (prices adjust so that supply = demand).
- Derive "short run" elasticities, holding labor allocations & expenditure shares constant

$$\frac{\partial \ln p_{is}}{\partial \ln E^T} = \frac{X_{is}^T}{y_{is}} + \sum_n \frac{v_n}{y_{is}} \pi_{nis} \sum_j \sigma_{nj} \frac{\partial \ln w_j}{\partial \ln E^T}$$

$$\frac{\partial \ln w_i}{\partial \ln E^T} = \frac{\sum_s X_{is}^T}{\sum_s y_{is}} + \sum_j \sum_s \sum_n \pi_{nis} \frac{\nu_n}{y_{is}} \sigma_{nj} \left(\frac{\sum_s X_{js}^T}{\sum_s y_{js}} \right) + \dots$$

- Zero-degree elasticities:

$$\frac{\partial \ln p_{is}}{\partial \ln E^T} = \frac{X_{is}^T}{y_{is}} \qquad \frac{\partial \ln w_i}{\partial \ln E^T} = \frac{\sum_s X_{is}^T}{\sum_s y_{is}}$$

- Note: In paper we do long run elasticities too using "exact hat"

Empirics

1. Deductive Approach
2. Inductive Approach
3. **Hybrid Approach**

Hybrid Approach

- Hybrid Regression Approach

$$\Delta \ln p_{ismt} = \gamma_{is} + \gamma_{ts} + \beta_s^{p,high} \times \mathbb{1}_{is}^{p,high} \times \Delta \log E_{imt}^T + \beta_s^{p,low} \times \mathbb{1}_{is}^{p,low} \times \Delta \log E_{imt}^T + \epsilon_{ismt}$$

$$\Delta \ln w_{imt} = \gamma_i + \gamma_t + \beta_s^{p,high} \times \mathbb{1}_i^{w,high} \times \Delta \log E_{imt}^T + \beta_s^{p,low} \times \mathbb{1}_i^{w,low} \times \Delta \log E_{imt}^T + \epsilon_{imt}$$

- where

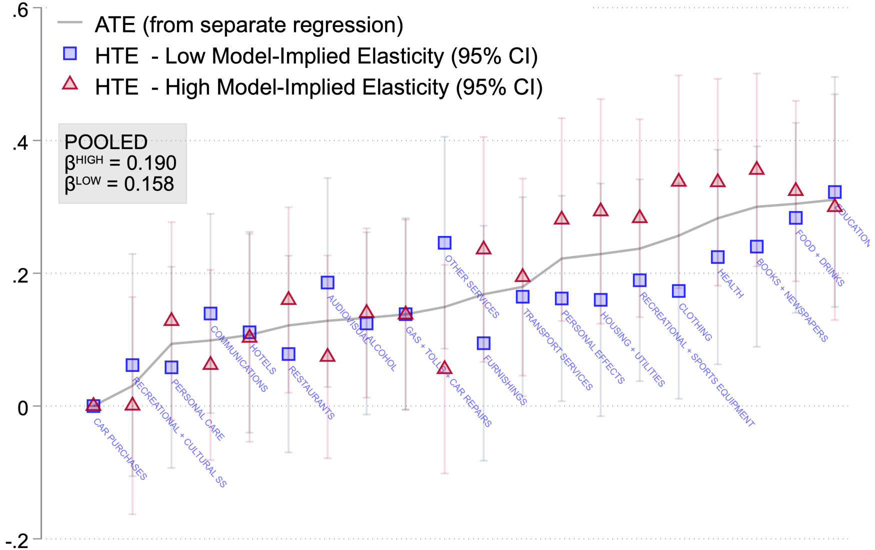
$$\mathbb{1}_{is}^{p,high} = \mathbb{1}\left\{\eta_{is}^p > median\left(\eta_{is}^p\right)|s\right\}$$

$$\mathbb{1}_{is}^{p,low} = \mathbb{1}\left\{\eta_{is}^p \leq median\left(\eta_{is}^p\right)|s\right\}$$

- η_{is}^p is predicted by
  1. 'Zero-degree' elasticities Price HTE Income HTE Maps
  2. Short Run Elasticities

- Non-parametrically identifies heterogenous treatment effects

Heterogeneous Price Effects by Sector



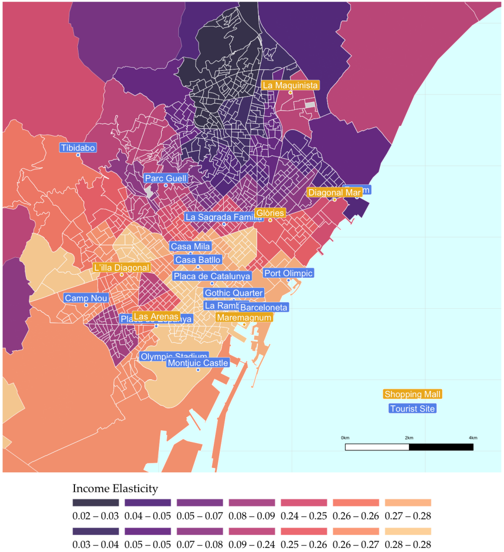
Heterogeneous Income Effects

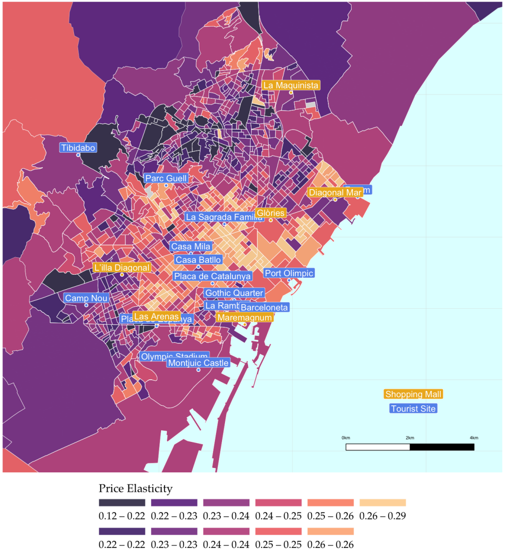
	(1) Baseline	(2) Zero	(3) SR	(4) DEK
S.ln(Tourist Expenditures)	0.0530**	-0.0396	0.00326	-0.0232
	(0.0173)	(0.0243)	(0.0109)	(0.0165)
x Tourist Share > Median		0.193*		
		(0.0822)		
x Short Run Wage Elasticity > Median			0.289**	
			(0.0940)	
x Long Run Wage Elasticity > Median				0.212***
				(0.0507)
Observations	24238	24238	24238	24238
IV	1	1	1	1
FE location-year	1	1	1	1
FE year-month-type	1	1	1	1
FE location-month	1	1	1	1

Standard errors in parentheses

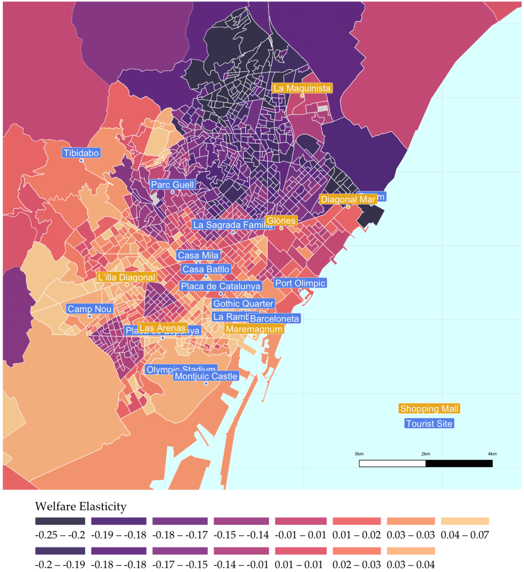
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Hybrid: SR Price and Income Effects





Hybrid: SR Welfare Effects



Is tourism good for locals?

- Welfare evaluation using the expression for welfare changes, i.e.

$$\frac{d \ln u_n}{\partial \ln E^T} = \sum_i \sigma_{ni} \frac{\partial \ln w_i}{\partial \ln E_i^T} - \sum_{i,s} \pi_{nis} \frac{\partial \ln p_{is}}{\partial \ln E_i^T}$$

- Results
  - On average: Welfare deterioration of 12%
  - Substantial heterogeneity (Preferred results: Hybrid SR)
    - 10th percentile: -14%
    - 90th percentile: +2%

Conclusion

Conclusion

- New Data: New intra-city spatial patterns of consumption for locals and tourists
- New Theory: Urban Ricardo-Viner model for intra-urban welfare analysis
- New Methodology: Estimate welfare effects by “hybrid” approach
- New Insights: On average tourism hurts locals, but large heterogeneity

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Appendix

Additional Data

- Idealista imputed data on housing price trends (Euro/m2)
  - Frequency: Monthly
  - Time Period: January 2010- June 2020
  - Spatial Resolution: Neighborhoods in Barcelona (Barrios)
  - Available for rental rates and housing prices

Back

Consumption of Locals

- Nested CES preferences across sectors and locations with elasticities $\{\sigma_s, \eta\}$

$$u_n = \frac{v_n}{\left(\sum_{s=0}^{S} \alpha_s \left(\left(\sum_{i=1}^{N} \gamma_{is} \tau_{isn}^{1-\sigma_s} p_{is}^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}}\right)^{1-\eta}\right)^{\frac{1}{1-\eta}}} B_n$$

- Demand function,

$$X_{isn} = \left(\frac{\tau_{isn}^{1-\sigma_s} p_{is}^{1-\sigma_s}}{\sum_j \tau_{jsn}^{1-\sigma_s} p_{js}^{1-\sigma_s}}\right) \alpha_{n,s} v_n$$

where $\alpha_{n,s}$ corresponds to the nested CES sectoral expenditure share

back

Consumption of Tourists

- For tourists we abstract from bilateral trade costs and define symmetrically,

$$X_{is}^{T} = \left(\frac{\gamma_{is}^{T} p_{is}^{1-\sigma_s}}{\sum_j \gamma_{js}^{T} p_{js}^{1-\sigma_s}} \right) \alpha_s^{T} E^{T},$$

where α_s^T corresponds to the nested CES sectoral expenditure share

back

Production and Labor supply

- Production with a Cobb-Douglas production function with a specific factor,

$$Q_{is} = A_{is} L_{is}^{\beta_s} K_{is}^{1-\beta_s}.$$

- Labor Supply is defining disposable income,

$$v_n = \left(\sum_i \mu_{ni}^{-\theta} w_i^{\theta} \right)^{\frac{1}{\theta}}$$

- which generates

$$L_{ni} = \frac{\mu_{ni}^{-\theta} w_i^{\theta}}{\sum_{i,s} \mu_{ni}^{-\theta} w_i^{\theta}} L_n$$

back

Equilibrium

For any initial distribution of residential labor endowment $\{R_i\}$, a given level tourist expenditures $\{E^T\}$, a given level of sector-location factor endowment $\{M_{is}\}$, parameters defining the preference and production structure $\{\sigma_s, \eta, \alpha_s, \beta_s, \theta\}$, and geography $\left\{A_{i,s}, \gamma_{is}, \gamma_{i,s}^T, \tau_{nis}, \mu_{ni}\right\}$, an equilibrium is $\{w_i, p_{is}\}$ s.t.

1. Sector-location specific market clearing

$$p_{is} Q_{is} = \sum_n \left(\frac{\tau_{isn}^{1-\sigma_s} p_{is}^{1-\sigma_s}}{\sum_j \tau_{jsn}^{1-\sigma_s} p_{js}^{1-\sigma_s}} \right) \alpha_s \left(\sum_i \mu_{ni}^{-\theta} w_i^{\theta} \right)^{\frac{1}{\theta}} + X_{is}^T$$

2. Labor Market clearing

$$L_i \sum_s \frac{1}{\beta_s} w_i \left(\frac{L_{is}}{L_i} \right) = \sum_s \sum_n \left(\frac{\tau_{isn}^{1-\sigma_s} p_{is}^{1-\sigma_s}}{\sum_j \tau_{jsn}^{1-\sigma_s} p_{js}^{1-\sigma_s}} \right) \alpha_s \left(\sum_i \mu_{ni}^{-\theta} w_i^{\theta} \right)^{\frac{1}{\theta}} + \sum_s X_{is}^T$$

back

Table: First Stage

	(1) S.ln Tourists Expenditures
Group Bartik	-0.989***
	(0.123)
Observations	24238
F	64.63
FE location-year	1
FE year-month	1
FE location-month	1

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

back

Inductive Approach: Exact Hat Algebra

- Goods market clearing condition

$$\hat{p}_{is}^{\frac{1}{1-\beta_s}}\hat{w}_i^{-\frac{\beta_s}{1-\beta_s}} = \sum_n \left(\frac{X_{nis}}{y_{is}}\right) \frac{\left(\left(\sum_{i=1}^N \pi_{nis}\hat{p}_{is}^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}}\right)^{1-\eta}}{\sum_{s=0}^S \left((\pi_{n,s})\left(\left(\sum_{i=1}^N \pi_{nis}\hat{p}_{is}^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}}\right)^{1-\eta}\right)} \frac{\hat{p}_{is}^{1-\sigma_s}}{\sum_j \pi_{jsn}\hat{p}_{js}^{1-\sigma_s}}$$

$$+ \frac{X_{is}^T}{y_{is}} \frac{\left(\left(\sum_{i=1}^N \pi_{is}^T\hat{p}_{is}^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}}\right)^{1-\eta}}{\sum_{s=0}^S \left(\pi_s^T\left(\left(\sum_{i=1}^N \pi_{is}^T\hat{p}_{is}^{1-\sigma_s}\right)^{\frac{1}{1-\sigma_s}}\right)^{1-\eta}\right)} \frac{\hat{p}_{is}^{1-\sigma_s}}{\sum_j \left(\pi_{js}^T\right)\hat{p}_{js}^{1-\sigma_s}}\hat{E}^T, \tag{3}$$

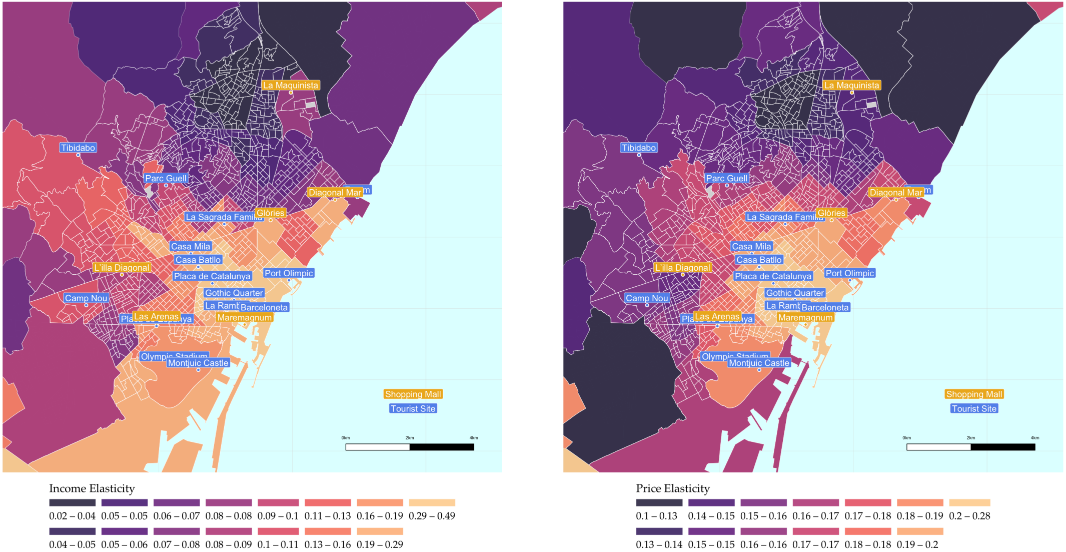
- Labor Market clearing condition,

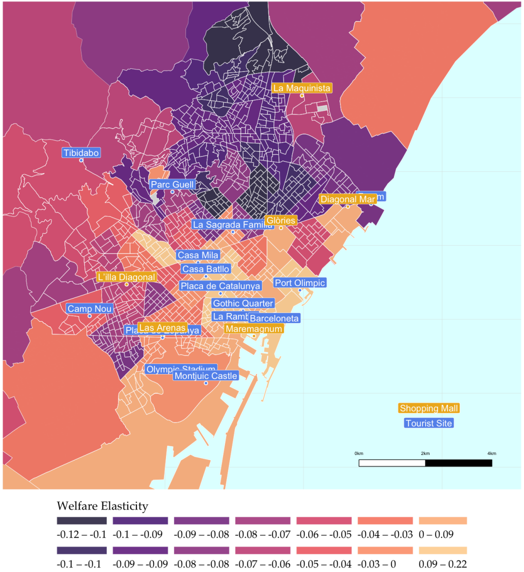
$$\sum_s \left(\frac{\beta_s y_{is}}{\sum_s \beta_s y_{is}}\right)\hat{p}_{is}^{\frac{1}{1-\beta_s}}\hat{w}_i^{-\frac{\beta_s}{1-\beta_s}} = \sum_n \sigma_{ni}\left(\frac{R_n w_i}{\sum_s \beta_s y_{is}}\right)\frac{\hat{w}_i^{1+\theta}}{\sum_j \sigma_{nj}\hat{w}_j^{\theta}}.$$

Inductive Approach: Calibration

- Factor share of labor, $\beta_s = .66$
- Labor Supply elasticity $\theta = 3.3$ (Monte et al.; 2018)
- Lower nest elasticity of substitution $\sigma_s = 3.9$ (Hottman et al.; 2016)
- Upper nest elasticity of substitution $\eta = 1.8$

back


La Maquinista
Tibidabo
Parc Guell
Diagonal Mar
La Sagrada Familia
Glòries
Casa Mila
Casa Batllo
L'illa Diagonal
Placa de Catalunya
Port Olimpic
Camp Nou
Gothic Quarter
Barceloneta
Las Arenas
Maremagnum
Olympic Stadium
Montjuic Castle
Shopping Mall
Tourist Site
0km
2km
4km
Income Elasticity
0.02 – 0.04
0.05 – 0.05
0.06 – 0.07
0.08 – 0.08
0.09 – 0.1
0.11 – 0.13
0.16 – 0.19
0.29 – 0.49
0.04 – 0.05
0.05 – 0.06
0.07 – 0.08
0.08 – 0.09
0.1 – 0.11
0.13 – 0.16
0.19 – 0.29
Price Elasticity
0.1 – 0.13
0.14 – 0.15
0.15 – 0.16
0.16 – 0.17
0.17 – 0.18
0.18 – 0.19
0.2 – 0.28
0.13 – 0.14
0.15 – 0.15
0.16 – 0.16
0.17 – 0.17
0.18 – 0.18
0.19 – 0.2



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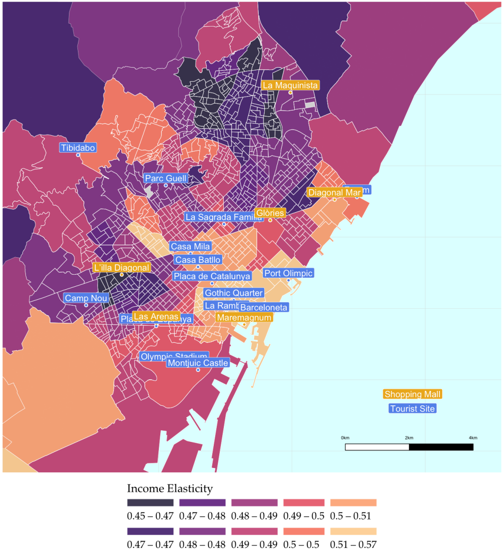
Gothic Quarter
Camp Nou
Barceloneta
Las Arenas
Maremagnum
Montjuic Castle
Shopping Mall
Tourist Site
0km
2km
4km
Welfare Elasticity
-0.12 – -0.1
-0.1 – -0.09
-0.09 – -0.08
-0.08 – -0.07
-0.06 – -0.05
-0.04 – -0.03
0 – 0.09
-0.1 – -0.1
-0.09 – -0.09
-0.08 – -0.08
-0.07 – -0.06
-0.05 – -0.04
-0.03 – 0
0.09 – 0.22

back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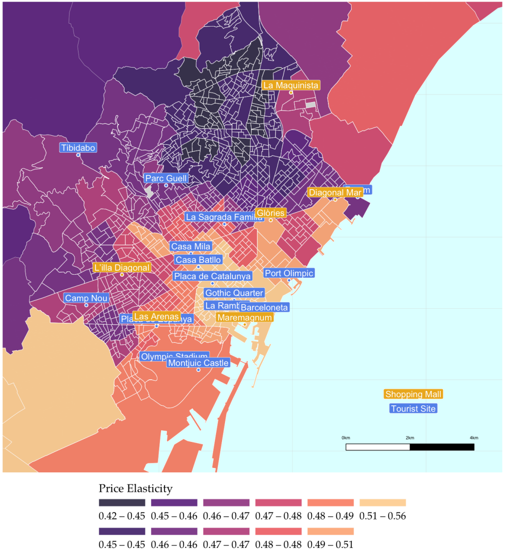
Maremagnum
Montjuic Castle
Shopping Mall
Tourist Site
0km
2km
4km
Income Elasticity
0.45 – 0.47
0.47 – 0.48
0.48 – 0.49
0.49 – 0.5
0.5 – 0.51
0.47 – 0.47
0.48 – 0.48
0.49 – 0.49
0.5 – 0.5
0.51 – 0.57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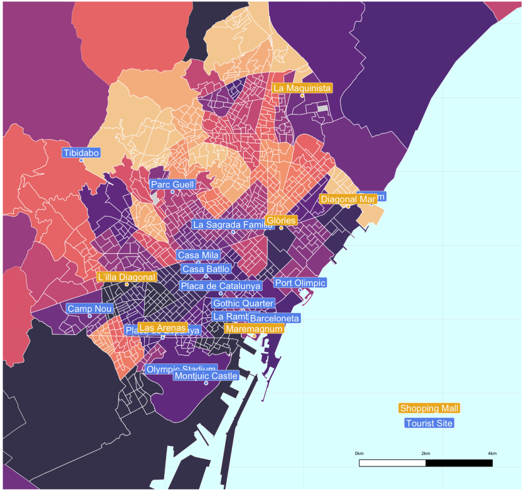
Tourist Site
0km
2km
4km
Price Elasticity
0.42 – 0.45
0.45 – 0.46
0.46 – 0.47
0.47 – 0.48
0.48 – 0.49
0.51 – 0.56
0.45 – 0.45
0.46 – 0.46
0.47 – 0.47
0.48 – 0.48
0.49 – 0.51



Welfare Changes

-0.39 – 0.06pc
0.18 – 0.25pc
0.32 – 0.42pc
0.52 – 0.61pc
0.71 – 0.85pc
0.99 – 1.17pc
1.28 – 1.42pc
1.64 – 2.81pc
0.06 – 0.18pc
0.25 – 0.32pc
0.42 – 0.52pc
0.61 – 0.71pc
0.85 – 0.99pc
1.17 – 1.28pc
1.42 – 1.64pc

back

Bartik

- Local Expenditure growth can be decomposed into,

$$g_i^T = \underbrace{\sum_g \varsigma_{i,g|i} \times g_{E_g}^T}_{\text{Group Composition}} + \underbrace{\sum_g \sum_s \varsigma_{i,s,g|i} \times g_{\kappa,s,g}^T}_{\text{Seasonal Demand}}$$

- initial group composition and initial consumption shares are given by,

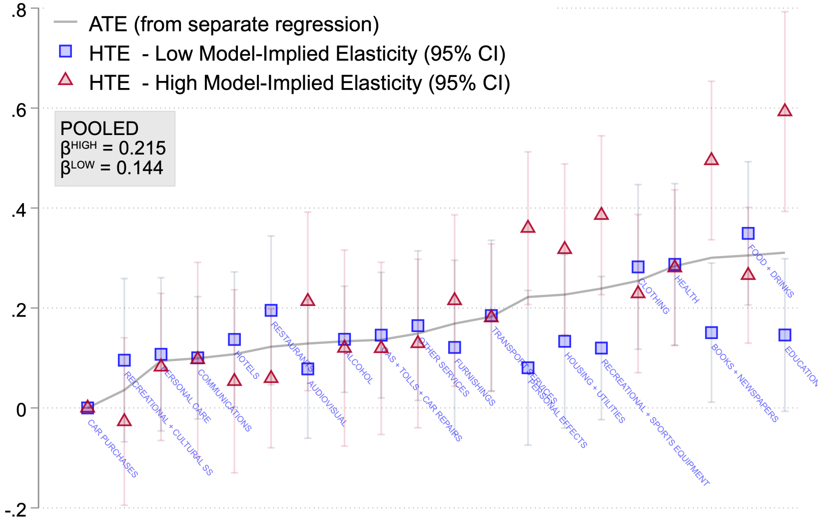
$$\varsigma_{i,s,g|i} \equiv \frac{E_{i,s,g}^T}{E_i^T} \quad \varsigma_{i,g|i} \equiv \frac{E_{i,g}^T}{E_i^T}$$

- and where changes in total group's income and in within-group category spending are given by,

$$g_{E_g}^T \equiv \frac{\Delta E_g^T}{E_g^T} \quad g_{\kappa,sg}^T = \frac{\Delta \kappa_{sg}^T}{\kappa_{sg}^T}$$

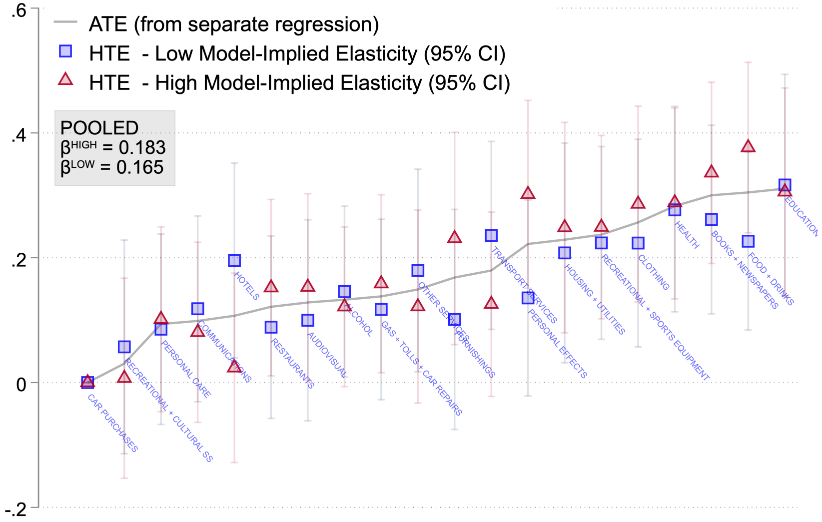
- Initial Shares exogenous i.e. orthogonal to local amenity shifts (Goldsmith-Pinkham et al.; 2018)

back



ATE (from separate regression)
HTE - Low Model-Implied Elasticity (95% CI)
HTE - High Model-Implied Elasticity (95% CI)
POOLED
β^HIGH = 0.215
β^LOW = 0.144
.8
.6
.4
.2
0
-.2
CAR PURCHASES
RECREATIONAL + CULTURAL SS
PERSONAL CARE
COMMUNICATIONS
HOTELS
RESTAURANTS
AUDIOVISUAL
ALCOHOL
GAS + TOLLS + CAR REPAIRS
OTHER SERVICES
FURNISHINGS
TRANSPORT SERVICES
PERSONAL EFFECTS
HOUSING + UTILITIES
RECREATIONAL + SPORTS EQUIPMENT
CLOTHING
HEALTH
BOOKS + NEWSPAPERS
FOOD + DRINKS
EDUCATION

back


.6
.4
.2
0
-.2
ATE (from separate regression)
HTE - Low Model-Implied Elasticity (95% CI)
HTE - High Model-Implied Elasticity (95% CI)
POOLED
βHIGH = 0.183
βLOW = 0.165
CAR PURCHASES
RECREATIONAL + CULTURAL SS
PERSONAL CARE
COMMUNICATIONS
HOTELS
RESTAURANTS
AUDIOVISUAL
ALCOHOL
GAS + TOLLS + CAR REPAIRS
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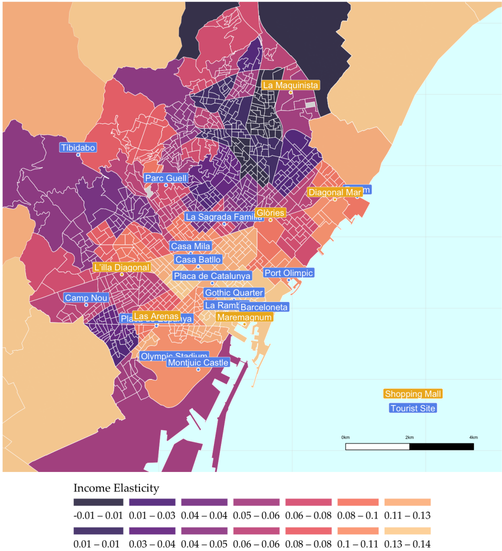
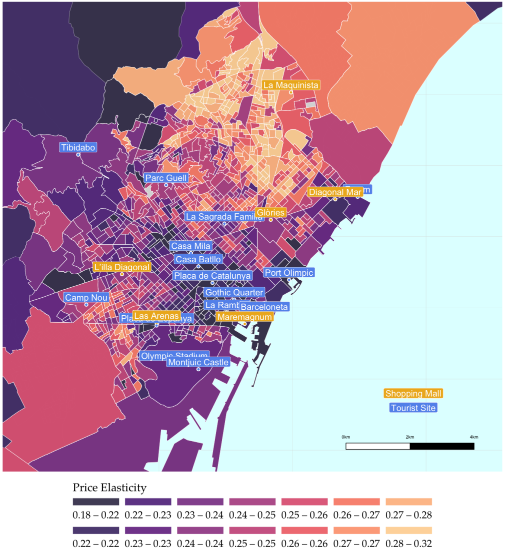
back


La Maquinista
Tibidabo
Parc Guell
Diagonal Mar
La Sagrada Familia
Glòries
Casa Mila
Casa Batllo
L'illa Diagonal
Placa de Catalunya
Port Olimpic
Camp Nou
Gothic Quarter
La Rambla
Barceloneta
Las Arenas
Maremagnum
Olympic Stadium
Montjuic Castle
Shopping Mall
Tourist Site
0km
2km
4km
Income Elasticity
-0.01 – 0.01
0.01 – 0.03
0.04 – 0.04
0.05 – 0.06
0.06 – 0.08
0.08 – 0.1
0.11 – 0.13
0.01 – 0.01
0.03 – 0.04
0.04 – 0.05
0.06 – 0.06
0.08 – 0.08
0.1 – 0.11
0.13 – 0.14


La Maquinista
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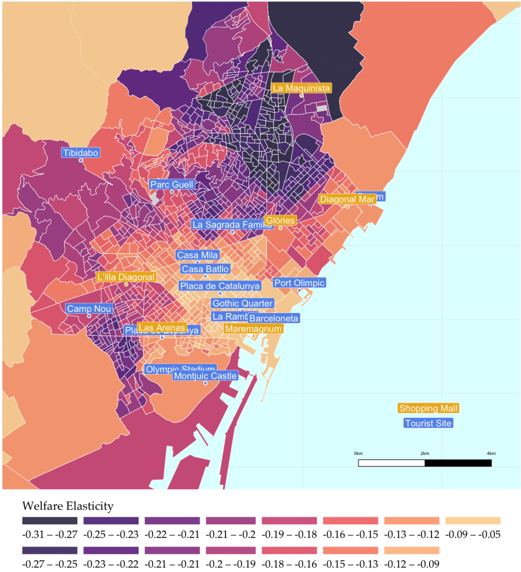
Las Arenas
Maremagnum
Olympic Stadium
Montjuic Castle
Shopping Mall
Tourist Site
0km
2km
4km
Price Elasticity
0.18 – 0.22
0.22 – 0.23
0.23 – 0.24
0.24 – 0.25
0.25 – 0.26
0.26 – 0.27
0.27 – 0.28
0.22 – 0.22
0.23 – 0.23
0.24 – 0.24
0.25 – 0.25
0.26 – 0.26
0.27 – 0.27
0.28 – 0.32



La Maquinista
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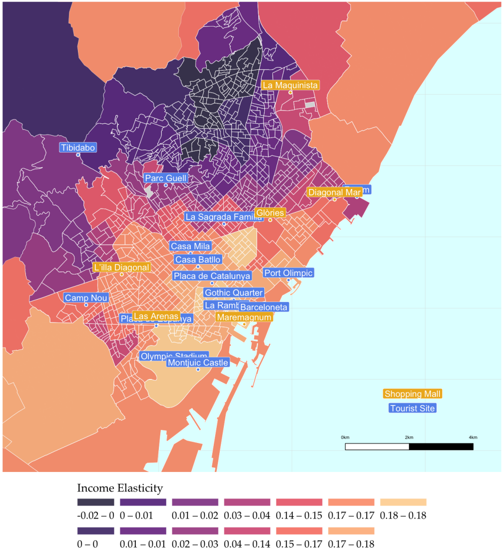
Maremagnum
Olympic Stadium
Montjuic Castle
Shopping Mall
Tourist Site
0km
2km
4km
Welfare Elasticity
-0.31 – -0.27
-0.25 – -0.23
-0.22 – -0.21
-0.21 – -0.2
-0.19 – -0.18
-0.16 – -0.15
-0.13 – -0.12
-0.09 – -0.05
-0.27 – -0.25
-0.23 – -0.22
-0.21 – -0.21
-0.2 – -0.19
-0.18 – -0.16
-0.15 – -0.13
-0.12 – -0.09


La Maquinista
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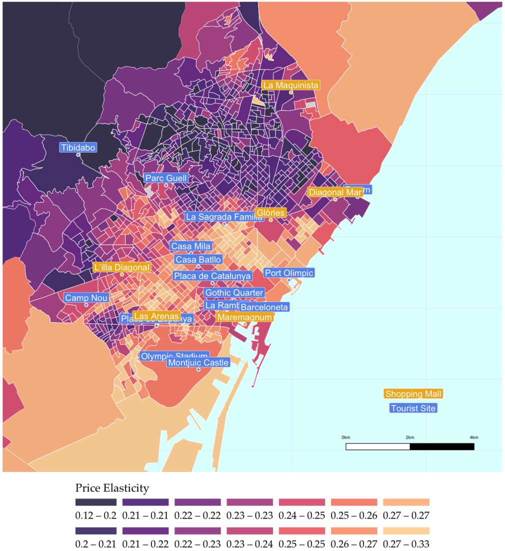
Barceloneta
Las Arenas
Maremagnum
Olympic Stadium
Montjuic Castle
Shopping Mall
Tourist Site
0km
2km
4km
Income Elasticity
-0.02 – 0
0 – 0.01
0.01 – 0.02
0.03 – 0.04
0.14 – 0.15
0.17 – 0.17
0.18 – 0.18
0 – 0
0.01 – 0.01
0.02 – 0.03
0.04 – 0.14
0.15 – 0.17
0.17 – 0.18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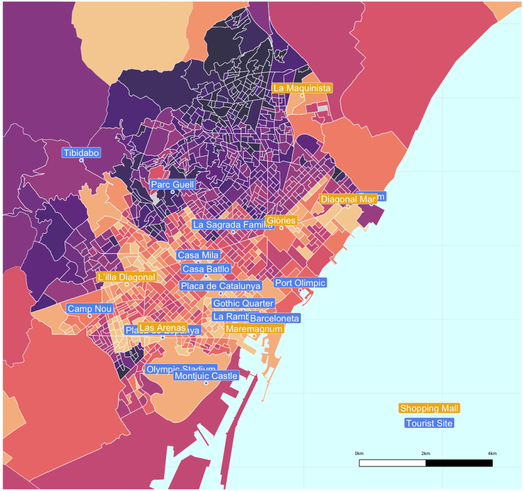
Las Arenas
Maremagnum
Olympic Stadium
Montjuic Castle
Shopping Mall
Tourist Site
0km
2km
4km
Price Elasticity
0.12 – 0.2
0.21 – 0.21
0.22 – 0.22
0.23 – 0.23
0.24 – 0.25
0.25 – 0.26
0.27 – 0.27
0.2 – 0.21
0.21 – 0.22
0.22 – 0.23
0.23 – 0.24
0.25 – 0.25
0.26 – 0.27
0.27 – 0.33



Welfare Elasticity

-0.32 – -0.22
-0.21 – -0.21
-0.2 – -0.2
-0.19 – -0.18
-0.12 – -0.1
-0.09 – -0.09
-0.08 – -0.08
-0.06 – -0.02
-0.22 – -0.21
-0.21 – -0.2
-0.2 – -0.19
-0.18 – -0.12
-0.1 – -0.09
-0.09 – -0.08
-0.08 – -0.06

back

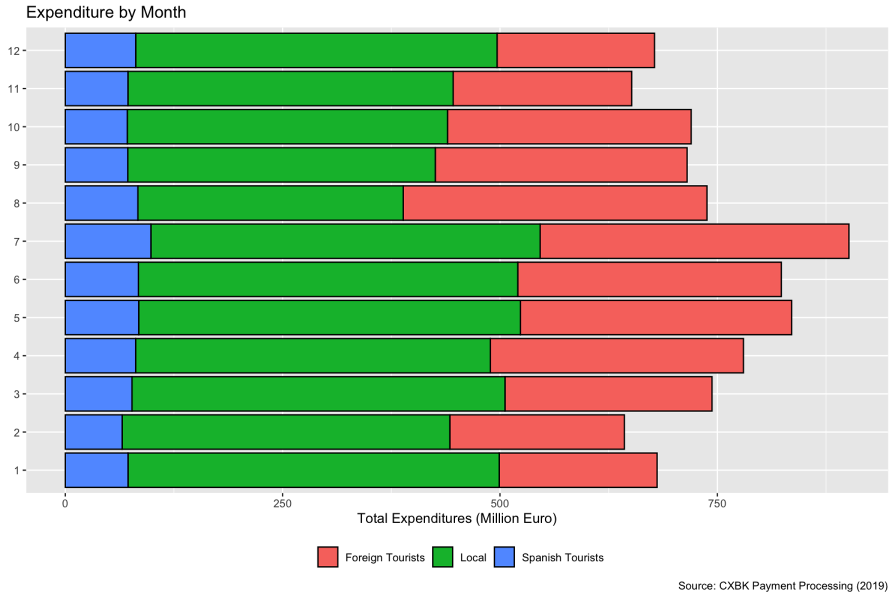
$$\Delta \ln w_{imt} = \gamma_{it} + \gamma_{im} + \gamma_{tm} + \beta^{w} \times \Delta \log E^{T}_{itm} + \epsilon_{imt},$$

	(1)
	S.ln Income
S.ln Tourists Expenditures	0.0530**
	(0.0173)
Observations	24238
IV Bartik	1
FE location-year	1
FE year-month	1
FE location-month	1

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

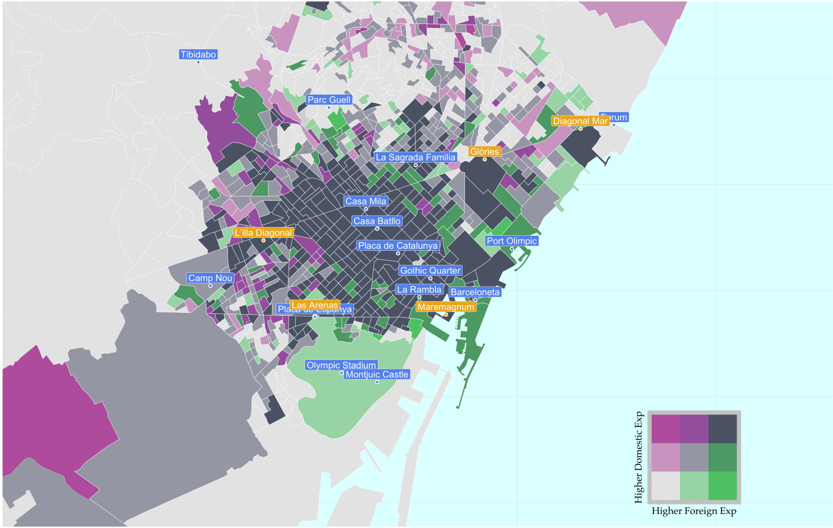
back



Expenditure by Month
12
11
10
9
8
7
6
5
4
3
2
1
0
250
500
750
Total Expenditures (Million Euro)
Foreign Tourists
Local
Spanish Tourists
Source: CXBK Payment Processing (2019)

back

Spanish Tourists vs Foreign Tourist Expenditures



Source: CXBK Payment Processing (2019)

back

Estimate gravity equation for commuting flows

$$\log(\sigma_{ij}) = \alpha \log(\tau_{ni}) + \gamma_n + \delta_i + \epsilon_{ni}$$

	(1) PPML	(2) OLS	(3) PPML	(4) OLS
Log(Distance)	-4.628***	-2.121***		
	(0.313)	(0.138)		
Distance			-0.485***	-0.127***
			(0.0294)	(0.0156)
Observations	11449	1633	11449	1633
FE: Origin	1	1	1	1
FE: Destination	1	1	1	1

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

back

Simple Theory: Overview

- Change in utility can be expressed as,

$$d \ln u_i = \partial \ln v_i - \sum_s \pi_{is} \partial \ln p_{is}$$

- Applying an envelope condition we can further simplify,

$$d \ln u_i = \sum_s (\sigma_{is} - \pi_{is}) \partial \ln p_{is}$$

  - Tourism is beneficial if i is a net producer of the tourist sector

- If residents allocate their labor to maximize income, we obtain,

$$d \ln v_n = \sum_{i,s} \sigma_{nis} \partial \ln w_{is},$$

back

Inductive Approach: Outline

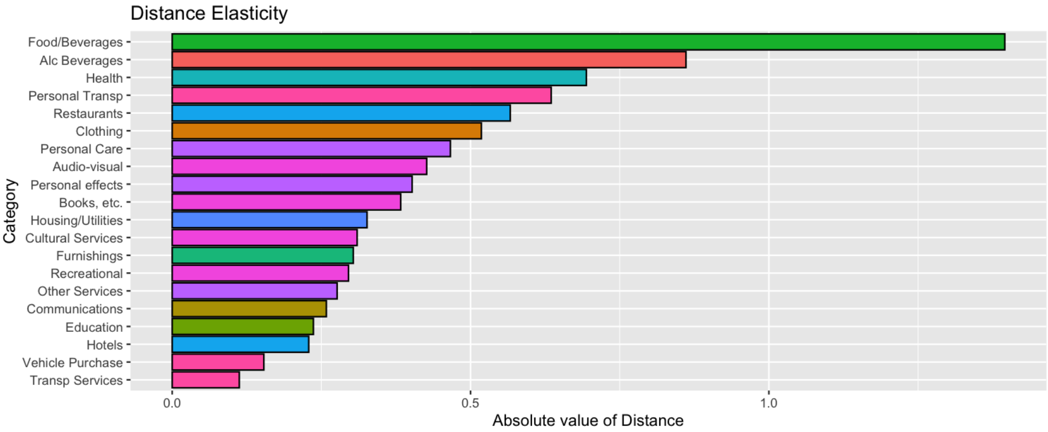
- Quantitative Urban Ricardo-Viner model in exact hat algebra DEK Equations
- Calibration using literature values Calibration
- Two exercises:
  - Short-run impact: Adjustment of consumption only DEK SR Results
  - Long-run impact: Adjustment of both consumption and labor allocations

back

Stylized Facts

Estimate gravity equation for consumption flows

$$\log \pi_{nis} = \phi_s \log \tau_{ni} + \log \delta_{n,s} + \log \delta_{i,s} + u_{ni,s},$$



Source: CXBK Payment Processing (2019)