Urban Welfare: Tourism in Barcelona

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NBER SI - Real Estate/Urban
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New Generation of Urban Data

Beyond geographical disaggregation: Spending, mobility, income **networks**

- New opportunities:
- New challenges:

New Generation of Urban Data

Beyond geographical disaggregation: Spending, mobility, income **networks**

- New opportunities: Relax parametric assumptions + structural estimation in urban quantitative models
- New challenges: Incorporate spatial GE effects, measure welfare in empirical analysis

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Beyond geographical disaggregation: Spending, mobility, income **networks**

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This Paper

1. General empirical method to estimate **heterogeneous welfare effects of urban shock**
   - Regression based: No parametric assumptions or structural estimation
   - Use theory to define welfare + incorporate heterogeneity and GE effects across space
2. Apply methodology to estimate welfare effect of tourism in Barcelona
   - Rich new data on expenditure and income spatial patterns
   - Causal identification from variation in vacation timing in RoW

Key Findings

1. Methodological
    - Simple reduced form approach has problems (Aggr. bias + SUTVA violation)
    - Our augmented reduced-form approach identifies heterogeneity + GE effects
    - ... and does as well as full structural model
2. Impact of tourism
    - Median resident not substantially affected by (seasonal changes in) tourism...
    - ...but there is substantial heterogeneity with winners and losers
    - Both heterogeneity in tourist spending and GE spillovers matter

Outline of Talk

A General Methodology for (small) Urban Shocks

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Welfare Effects Across the City

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Theory (In A Nutshell)

- N blocks, each with resident(s) and firm(s)

1. Resident of $n = 1, ..., N$ optimally chooses cons. and labor supply in $i = 1, ..., N$
    - Envelope theorem to optimization problems yields **analytical welfare**

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$$\mathbf{d} \ln \mathbf{u}\mathit{tility}_n = \underbrace{\sum_i \mathbf{c}\mathit{ommuting}_{n \to i} \times \partial \ln \mathbf{w}\mathit{ages}_i}_{\Delta \text{Spatial Income}} - \underbrace{\sum_i \mathbf{s}\mathit{pending}_{n \to i} \times \partial \ln \mathbf{p}\mathit{rices}_i}_{\Delta \text{Spatial Price Index}}$$

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2. Consider a demand shock $d \ln \mathbf{E}^T$ to locations $i = 1, ..., N$
   - Perturbation of market clearing allows to characterize short-run elasticities

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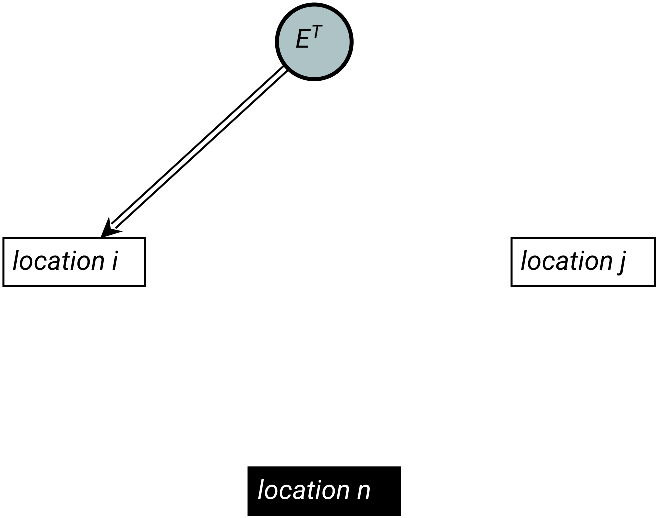
$$\begin{aligned} d \ln \mathbf{p} &= \mathcal{D}(E^T/y) \times d \ln \mathbf{E^T} + \mathcal{I}(\mathbf{S}, \mathbf{C}) \times d \ln \mathbf{w} \\ d \ln \mathbf{w} &= \underbrace{\mathcal{D}(E^T/y)}_{\textbf{Direct Effect} \propto \text{ rel. size}} \times \underbrace{(\mathbf{I} - \mathcal{I}(\mathbf{S}, \mathbf{C}))^{-1}}_{\textbf{Indirect Effect}\text{: Spatial Multiplier}} \times d \ln \mathbf{E^T} \end{aligned}$$

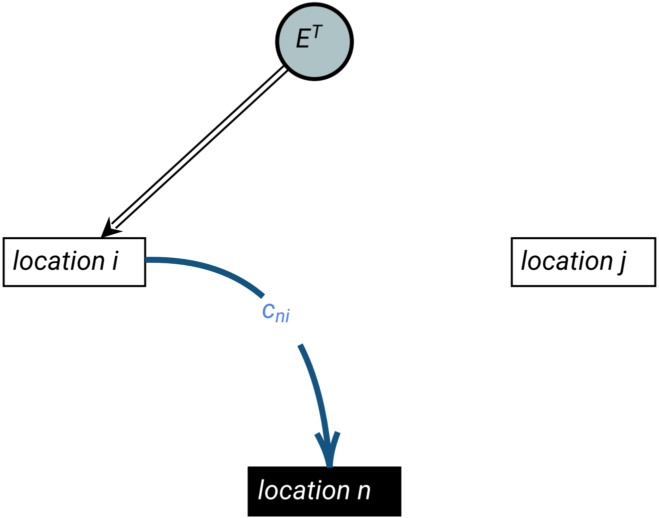
Intuition: Heterogeneous Effects & GE Spillovers

Consider an external **demand shock** E^T to a city



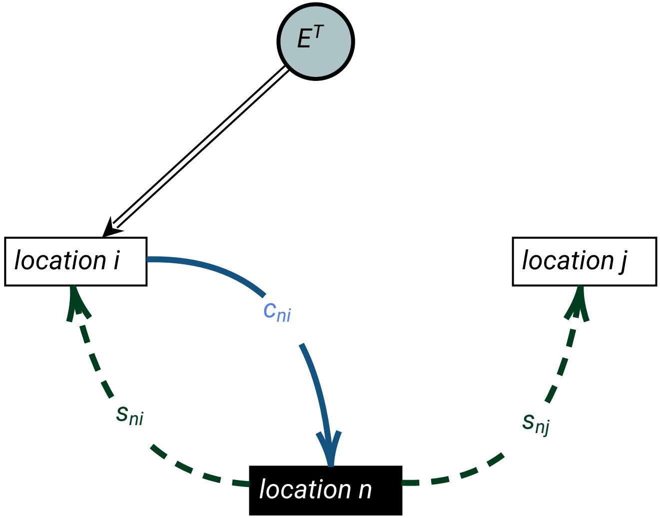
Intuition: Heterogeneous Effects & GE Spillovers

Consider an external **demand shock** E^T to a city $\rightarrow$ **Income Shock**



Intuition: Heterogeneous Effects & GE Spillovers

Consider an external **demand shock** E^T to a city $\rightarrow$ **Income Shock** $\rightarrow$ **Demand**



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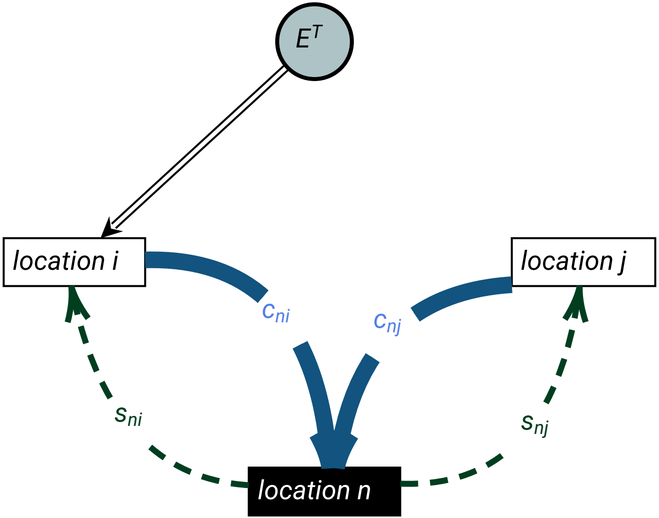
Consider an external **demand shock** E^T to a city $\rightarrow$ **Income Shock** $\rightarrow$ **Demand** $\rightarrow$ **Income Shock**



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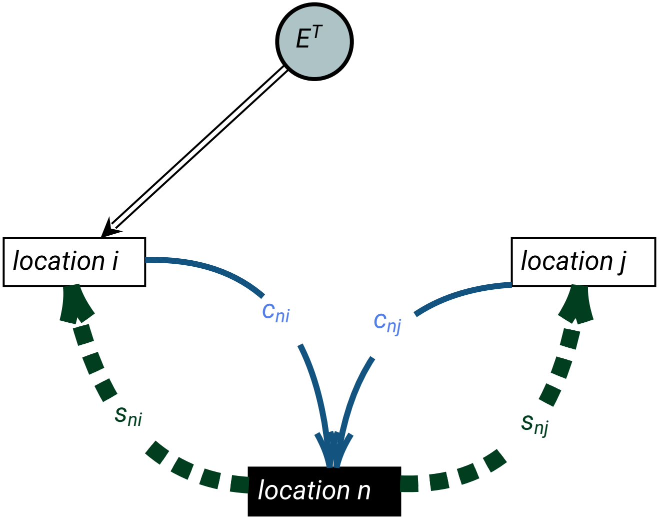

Evaluating the welfare effects of an urban shock requires

- Consumption share data $\mathbf{S} \equiv \{s_{ni}\}_{n=1,i=1}^{N,N}$
- Income share data $\mathbf{C} \equiv \{c_{ni}\}_{n=1,i=1}^{N,N}$
- Estimates of key elasticities: $\{\partial \ln p_i, \partial \ln w_i\}_{i=1}^{N}$, which requires
  - a shock $d \ln E^T$ + exogenous variation (coming up)
  - measure of heterogeneity in shock size: $\{E_i^T/(E_i^T + E_i^R)\}_{i=1}^{N}$
  - measure of GE spatial spillovers: $\mathcal{I}(\mathbf{S}, \mathbf{C})$

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High Resolution Data on Urban Consumption & Income Networks

Consumption Shares

- Source: **Caixabank**'s account & point-of-sale data (165M+ transactions pa) $\sim$ 54% of total exp. (HBS)
- Locals: 1095 residential tiles $\times$ 1095 cons tiles $\times$ 20 sectors $\times$ 36 months (1/2017 - 12/2019)
- Tourists: 15 *countries* of origin $\times$ 1095 cons tiles $\times$ 20 sectors $\times$ 36 months

Income Shares

- Source: **Caixabank**'s payrolls from over 400k accounts
- Mean, total, and median income per 1095 residential census tract Comparison: INE
- Combined with **mobility** patterns imputed from weekday lunches

Two Stylized Facts Towards Welfare Analysis

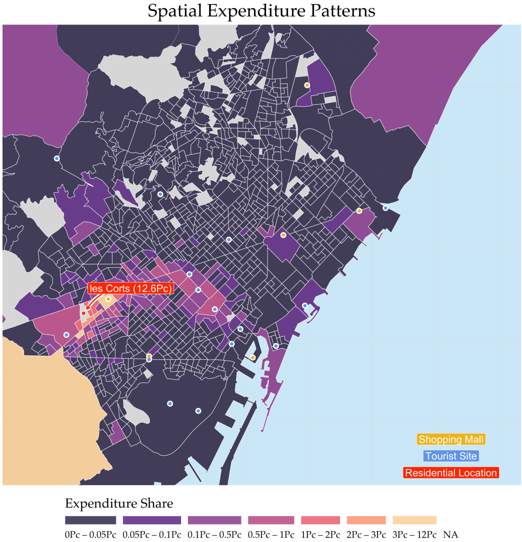
FACT 1: Locals' spending and income are spatially determined by residence

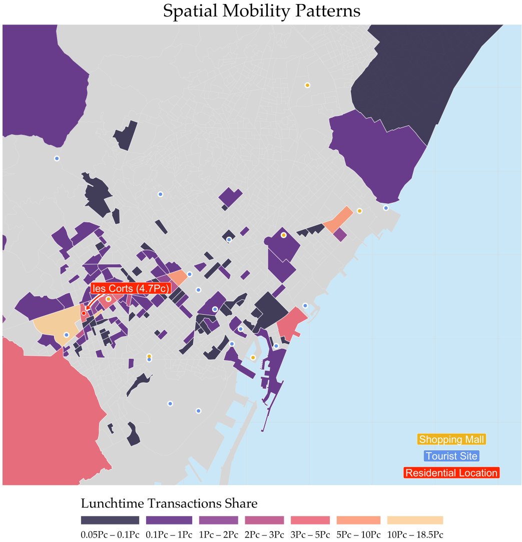
→ Consumption and Income shares

FACT 2: Tourist spending varies across space and time

→ Identification strategy

Fact 1: Locals spending and income patterns vary by residence

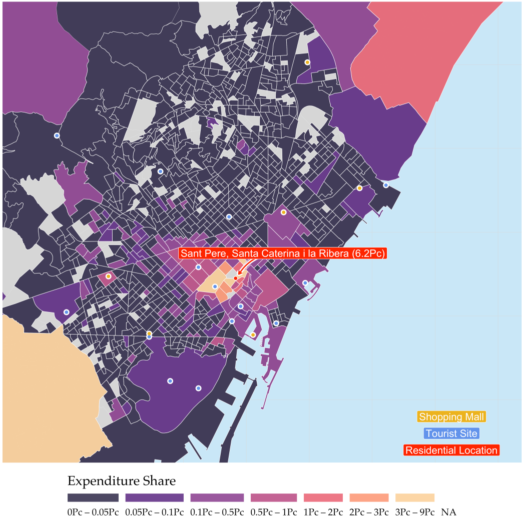




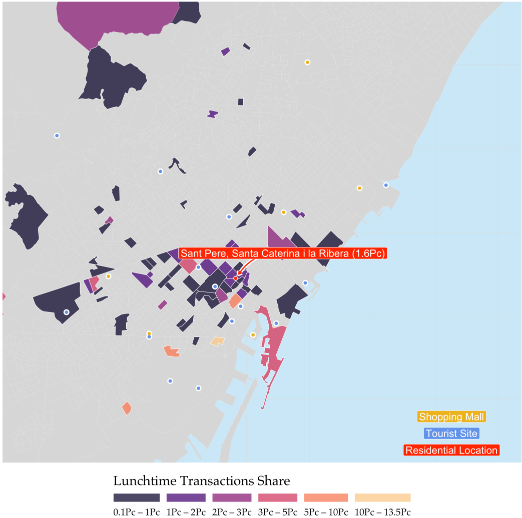
Cross-Sec. Local Spending
Cross-Sec. Income
Exp Gravity
Commuting Gravity

Fact 1: Locals spending and income patterns vary by residence

Spatial Expenditure Patterns



Spatial Mobility Patterns



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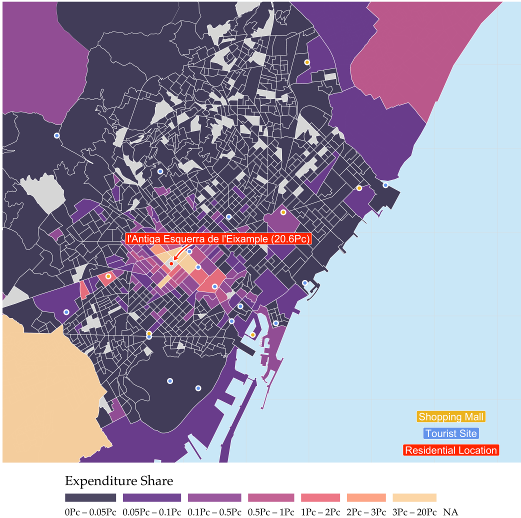

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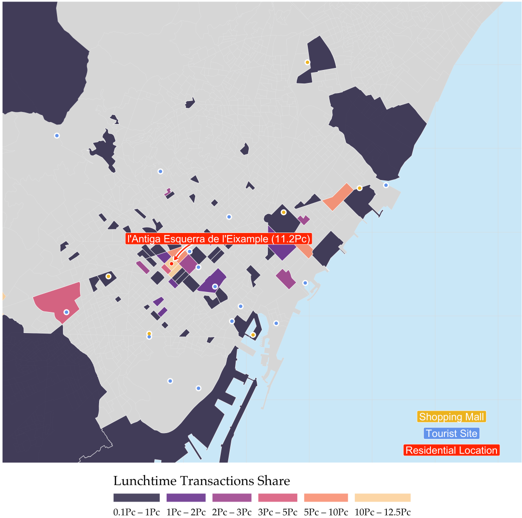

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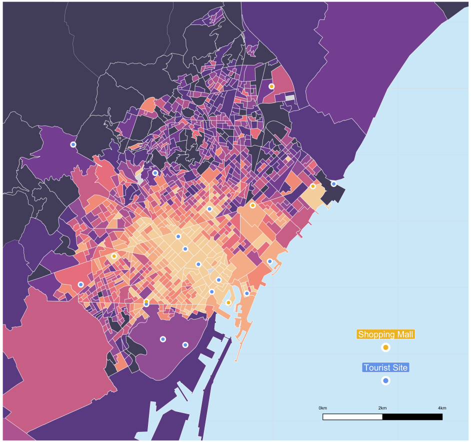
Fact 2: Tourist spending varies across space

Tourist Expenditures in Barcelona



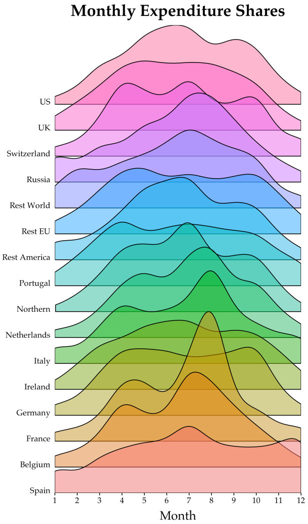
Average Yearly Expenditure per sqm in EUR

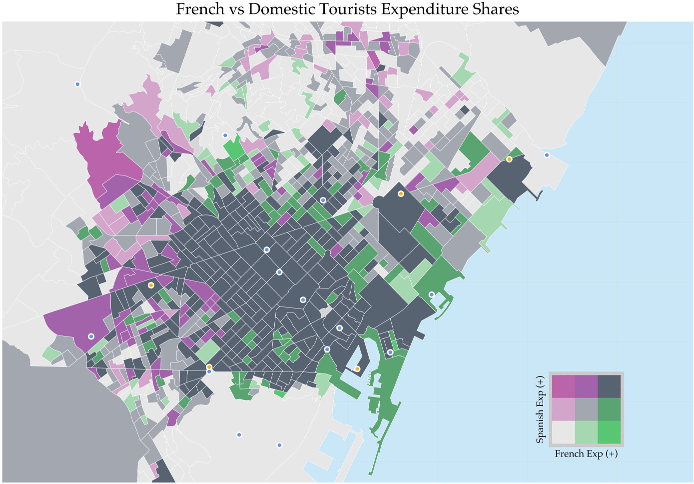
0 E/m2 – 0.7 E/m2
0.7 E/m2 – 1.6 E/m2
1.6 E/m2 – 2.6 E/m2
2.6 E/m2 – 3.8 E/m2
3.8 E/m2 – 6 E/m2
6 E/m2 – 9.4 E/m2
9.4 E/m2 – 17.4 E/m2
17.4 E/m2 – 32.3 E/m2
32.3 E/m2 – 70.3 E/m2
70.3 E/m2 – 2188.6 E/m2

Source: CXBK Payment Processing (2019)

Tourist Spending Time Series

...and time ...and type of tourist → Identification Strategy





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Price Regressions: Average and Heterogeneous Effects

- Regress $\ln Prices_{ist}$ on $\ln Expenditure_{it}^{Tourists}$

- Amenity-adjusted Prices = $\left(\frac{1}{1-\underbrace{\sigma}_{=5}}\right) \times$ gravity destination fixed effects

    ! Negative sign means positive effect on prices (and viceversa)

- Shift-share

    - Shift: spending of tourists from country ***k*** in month ***t* in the whole city of BCN**
    - Share: spending of tourists from country ***k*** in 2017's low season (Jan-March) in each tile ***i***

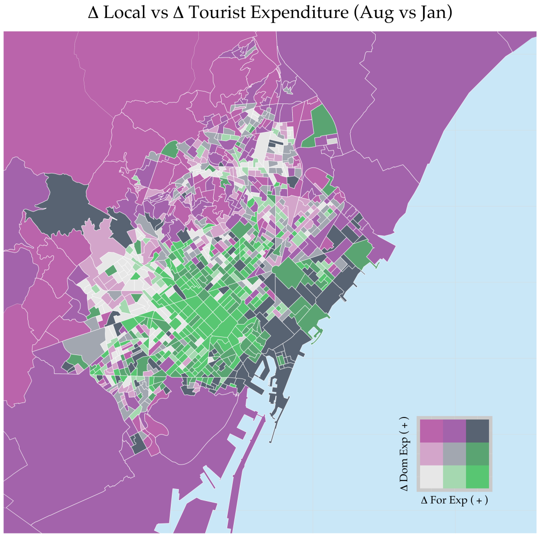
Price Regressions: Average and Heterogeneous Effects

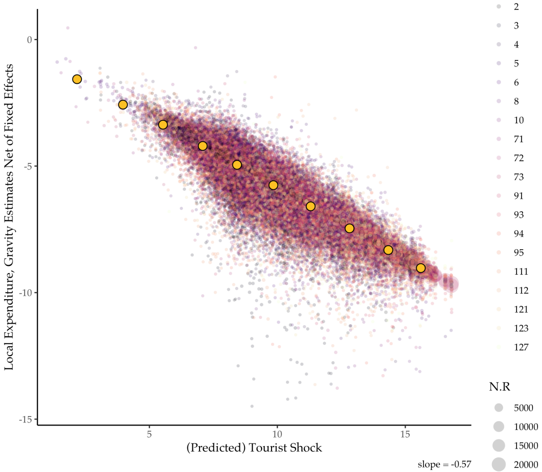
Dependent Variable: PPML Gravity Fixed Effects (*ist*)				
		IV - Ref: 2017 Low Season		
Independent Variables	OLS	**Average**	**Heterogeneous**	**G.E.**
$\widehat{\ln E^T_{it}}$	0.091***	**-0.668***	0.011	-0.037
Demand Shock E^T	(0.010)	**(0.223)**	(0.064)	(0.064)
$\widehat{\ln E^T_{it}} \times E^T_{it}/y$			**-0.628***	-0.555***
Heterogeneity on Direct E^T Size			**(0.091)**	(0.091)
$\widehat{\ln E^{GE}_{it}}(S, C)$				**-0.005***
Spatial GE Effects				**(0.0005)**
Fixed-effects	$t \times s, i \times s, i \times s \times year(t), i \times s \times month(t)$			
Observations	526,080	526,080	524,160	524,160
Adjusted R^2	0.998	0.997	0.975	0.975
F-test = t^2 (1st Stage)		30.7	30.7	30.7

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Group Estimates Rental Rate Estimates

Inside the Price Regressions





Income Regressions: Average and Heterogeneous Effects

- Regress $\ln Income_{nt}^{Residents}$ on $\ln CiExpenditure_{nt}^{Tourists}$
- *CiE* is Commuting-Implied Tourist Expenditure: $\sum_i c_{ni} \ln E_{it}^{T}$
  - Shock at residential tile (demand $\rightarrow$ income)
  - Theory consistent CiE Derivation
- Average $\rightarrow$ + heterogeneous **direct** effect $\rightarrow$ + spillovers **indirect** effect

Income Regressions: Average and Heterogeneous Effects

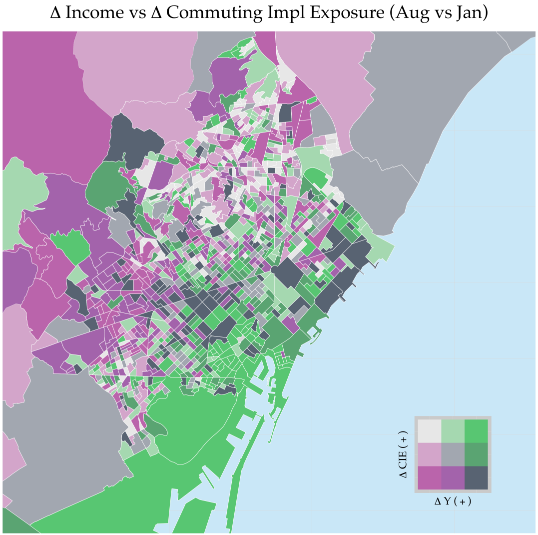
Dependent Variable: ln Mean Income (*nt*)

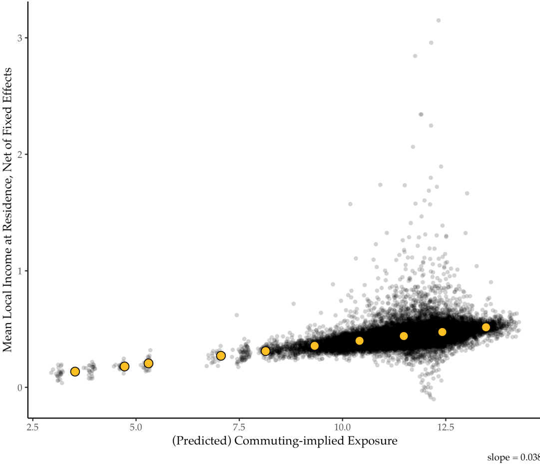
		IV - Ref: 2017 Low Season		
Indpendent Variables	OLS	**Average**	**Heterogeneous**	**G.E.**
$\widehat{\ln \text{CiE}}_{nt}$	0.006	**0.040****	-0.009	-0.008
Commuting-Implied Exposure to E^T	(0.004)	**(0.018)**	(0.025)	(0.025)
$\widehat{\ln \text{CiE}}_{nt} \times E^T/y$			**0.092*****	0.094***
Heterogeneity on Direct E^T Size			**(0.027)**	(0.031)
$\widehat{\ln \text{CiE}}^{GE}_{nt}(S, C)$				**-0.002**
Spatial GE Effects Spillovers				**(0.003)**
Fixed-effects	Location, Month, Year			
Observations	26472	26472	26472	26472
Adjusted R^2	0.888	0.888	0.888	0.893
F-test = t^2 (1st Stage)		927.0	927.0	927.0

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

ATE Results (Details) HTE Results (Details)

Inside the Income Regression





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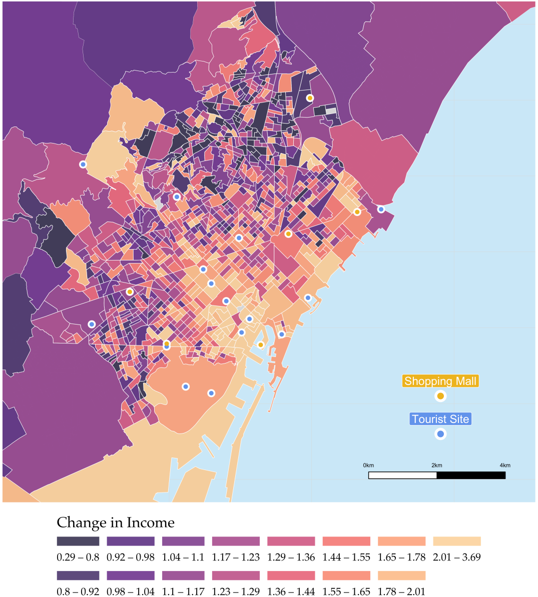
Welfare

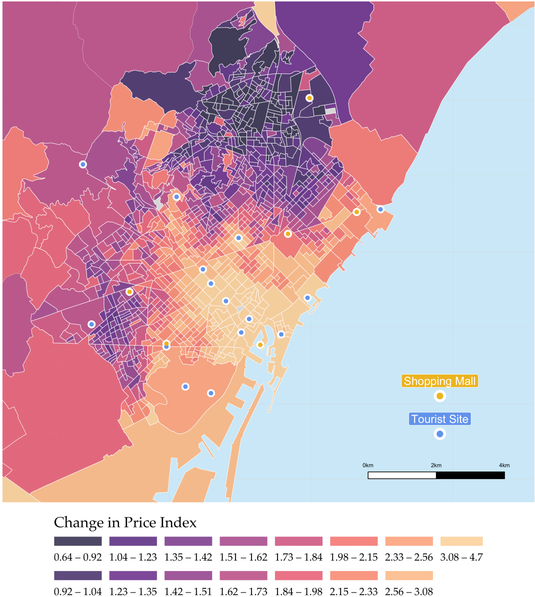
- Welfare Formula

$$d \ln u_n = \frac{\partial \ln v_n}{\partial \ln CiE_n^T} \times d \ln E_i^T - \sum_i s_{ni} \times \frac{\partial \ln p_i}{\partial \ln E_i^T} \times d \ln E_i^T$$

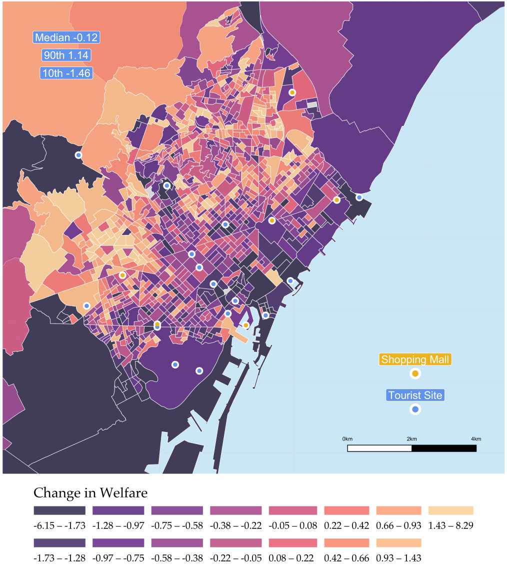
- s_{ni} use low-season baseline averages in 2017
- c_{ni} only one cross-section available
- Predict income and price changes from January to August using 2018, 19

Income (Panel A) and Price Effects (Panel B)



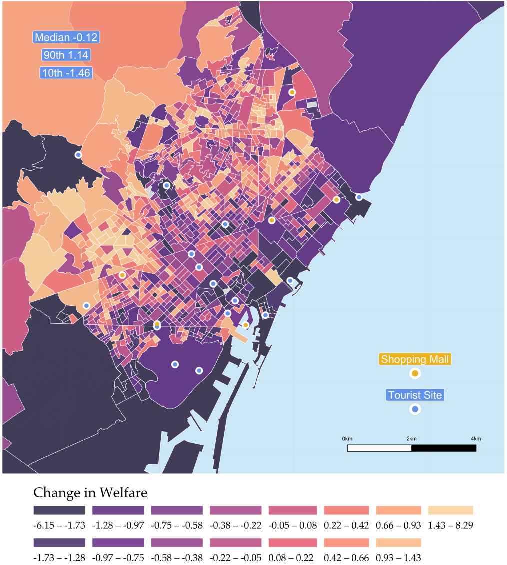


Welfare Effects (January to August)



Welfare Effects (January to August)

ATE: -5% (Aggregation bias + SUTVA violation)



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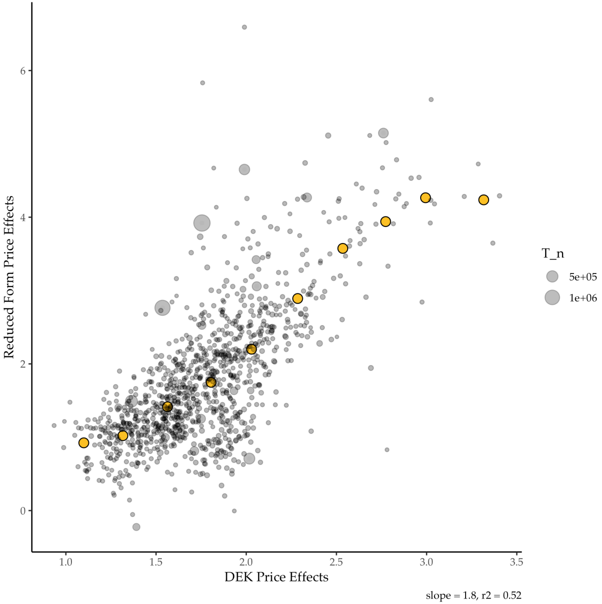
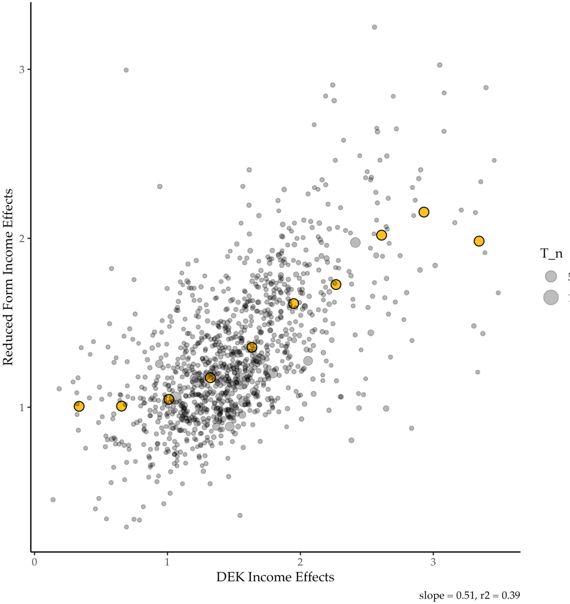
- Empirical method to estimate heterogeneous welfare within the city
  - If you have urban spending and income networks data

- More in the paper:
  - Housing prices regression (Idealista $\sim$ Spanish Zillow) Housing Reg.
  - Alternative commuting shares (more aggregated, using cellphone data)
  - Comparison with quantitative spatial equilibrium model Hat Algebra
  - Comparison with aggregate statistics and survey data Income Consumption

- Happening now:
  - Estimate EOS by sector (time-use gravity)
  - Improved income data (checking account movements rather than payroll)
  - (More) Aggregate shift: tourist inflows to the rest of Spain

Predictions highly correlated with Quantitative Model





Price Regressions Redux

Dependent Variable:	δ^R_{ist}		
	IV - Ref: 2017 Average		
Model:	(1)	(2)	(3)
Variables			
$\widehat{\ln E^T_{it}}$	0.011	2.63	-0.062
	(0.064)	(4.61)	(0.065)
$\widehat{\ln E^T_{it}} \times E^T/y$	-0.628***	-0.541***	-0.448***
	(0.091)	(0.179)	(0.102)
$\widehat{\ln E^{GE}_{it}}(S,C)$			-0.009***
			(0.002)
$\widehat{\ln E^T_{it}} \times \widehat{p}^{DEK}_i$		**-2.58**	
		(4.54)	
Fixed-effects			
Month-Year×Sector (480)	✓	✓	✓
Location×Sector (21,840)	✓	✓	✓
Location×Sector×Year (43,680)	✓	✓	✓
Location×Sector×Month (262,080)	✓	✓	✓
Fit statistics			
Observations	524,160	524,160	524,160
Adjusted R^2	0.975	0.975	0.975

Standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix

Literature

Urban Quantitative Spatial Economics

- Ahlfeldt *et al.* (2015), Monte *et al.* (2018), Allen & Arkolakis (2016), Heblich *et al.* (2020)

Big Data Spatial Economics

- Athey *et al.* (2020), Couture (2016), Couture *et al.* (2020), Davis *et al.* (2019), Agarwal *et al.* (2017), Miyauchi *et al.* (2021), Kreindler & Miyauchi (2021)

Impact of Tourism

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

First-Order Impact of Price Shocks

- Deaton (1989), Kim & Vogel (2020), Atkin *et al.* (2018), Baqaee & Burstein (2021)

Small shocks in general equilibrium

- Allen *et al.* (2020), Baqaee & Farhi (2019), Kleinman *et al.* (2020), Porto (2006)

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Commuting Implied Exposure Derivation

- Disposable income is given by

$$v_n = \sum_{i=1}^{N} w_i \ell_{ni}$$

- Totally differentiating and applying the envelope result from above, we obtain,

$$\mathrm{d} \ln v_n = \sum_{i=1}^{N} c_{ni} \mathrm{d} \ln w_i$$

- Impact of tourist expenditure shock,

$$\mathrm{d} \ln v_n = \sum_{i=1}^{N} c_{ni} \frac{\mathrm{d} \ln w_i}{\mathrm{d} \ln E^T} \mathrm{d} \ln E^T \qquad \ln \mathrm{CiE}_{ntm}^T = \sum_i c_{ni} \times \ln E_{itm}^T$$

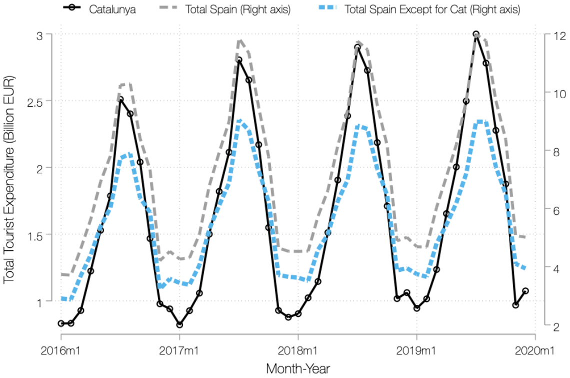
back

Tourism as an Urban Shock

- Large part of the economy
  - 7% of world exports
  - 330 million jobs
  - Spain: 11% of GDP

Tourism as an Urban Shock

- Large part of the economy
  - 7% of world exports
  - 330 million jobs
  - Spain: 11% of GDP
- Growing, especially in cities
  - BCN: 25% secular ↑ in past 5 yrs
  - BCN: 200% seasonal ↑ within year



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Tourism as an Urban Shock

- Large part of the economy
  - 7% of world exports
  - 330 million jobs
  - Spain: 11% of GDP
- Growing, especially in cities
  - BCN: 25% secular ↑ in past 5 yrs
  - BCN: 200% seasonal ↑ within year
- Unequal
  - Impact & Exposure
  - Welfare?

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Shift-Share Instrument: Derivations

- Representative tourist for group $\boldsymbol{g}$ has preferences,

$$u_g = \frac{E_g^T}{G(\tilde{\boldsymbol{p}})}$$

- Roy's identity gives expenditure shares
- Changes in tourist expenditure are:

$$dX_i^T = \sum_g s_{gi} dE_g^T + \sum_g s_{gi} db_{gi} + \sum_g s_{gi} dp_i$$

- Taking it to the data,

$$\Delta E_{imt}^T = \underbrace{\sum_g s_{gi} \times \Delta E_{gt}^T}_{\text{Group Composition}} + \epsilon_{imt}^T$$

- where $\epsilon_{imt}^T = \sum_g s_{gi} db_{gi} + \sum_g s_{gi} dp_i$

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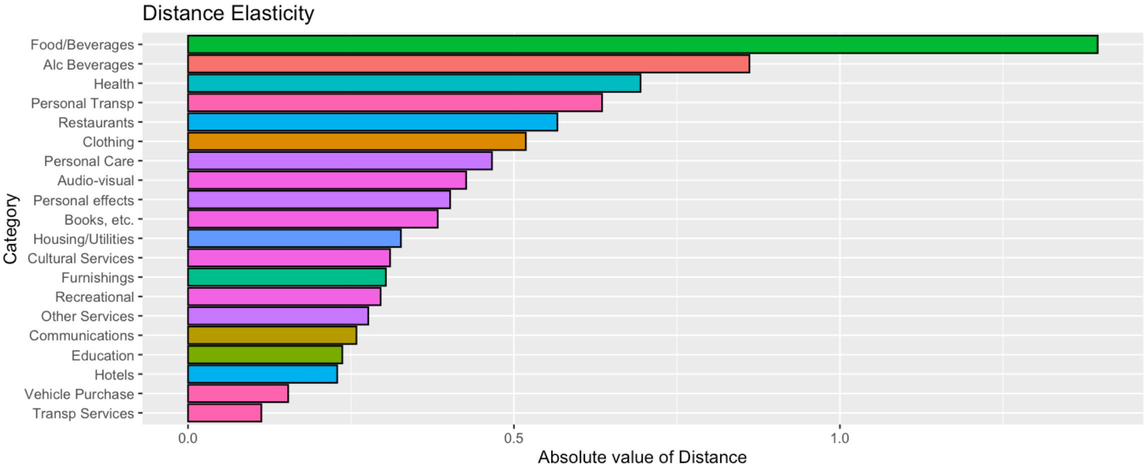
Distance Coefficient for Gravity by Sector



Source: CXBK Payment Processing (2019)

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Commuting Gravity Estimates

Dependent Variables:	commuters	log(commuters+1)	log(commuters)	transactions	log(transactions+1)	log(transactions)
	Cell Phone			Lunchtime		
Model:	(1) Poisson	(2) OLS	(3) OLS	(4) Poisson	(5) OLS	(6) OLS
Variables						
ldist	-4.48***	-1.51***	-1.17***	-1.53***	-0.134***	-0.411***
	(0.107)	(0.037)	(0.054)	(0.028)	(0.002)	(0.012)
Fixed-effects						
Origin	✓	✓	✓			
Destination	✓	✓	✓			
Origin (CT)				✓	✓	✓
Destination (CT)				✓	✓	✓
Fit statistics						
Observations	24,025	24,025	2,162	1,051,159	1,216,609	42,086
Pseudo R^2	0.798	0.117	0.193	0.598	0.343	0.091

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Housing Price Regressions

Dependent Variables:	HPRICE				RENT			
	IV - Ref: 2017 Average		IV - Ref: 2017 Low Season		IV - Ref: 2017 Average		IV - Ref: 2017 Low Season	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
$\widehat{\log E_{it}^{T}}$	0.059***	0.028***	0.059***	0.028***	0.043***	0.008*	0.044***	0.009*
	(0.016)	(0.005)	(0.016)	(0.005)	(0.013)	(0.005)	(0.013)	(0.005)
Fixed-effects								
i (108)	✓	✓	✓	✓	✓	✓	✓	✓
i×month (1,296)	✓		✓		✓		✓	
i×year (216)		✓		✓		✓		✓
Fit statistics								
Observations	2,592	2,592	2,592	2,592	2,592	2,592	2,592	2,592
Adjusted R^2	0.983	0.993	0.983	0.993	0.933	0.952	0.933	0.952

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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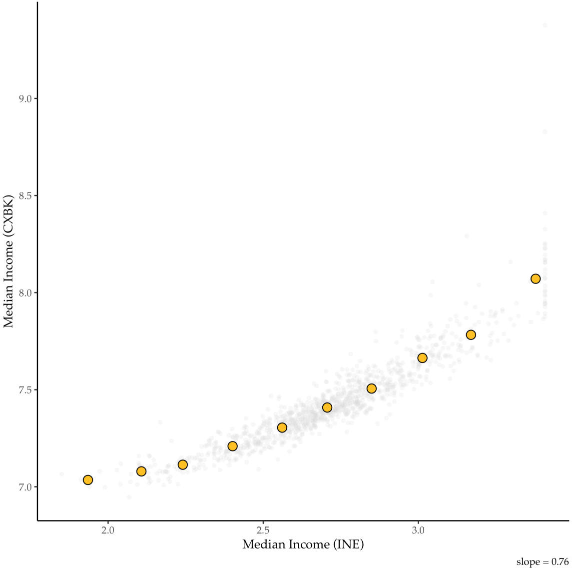
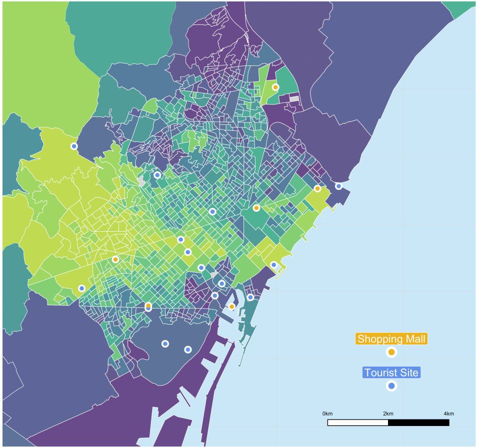
Income Data: Comparison with Administrative Data



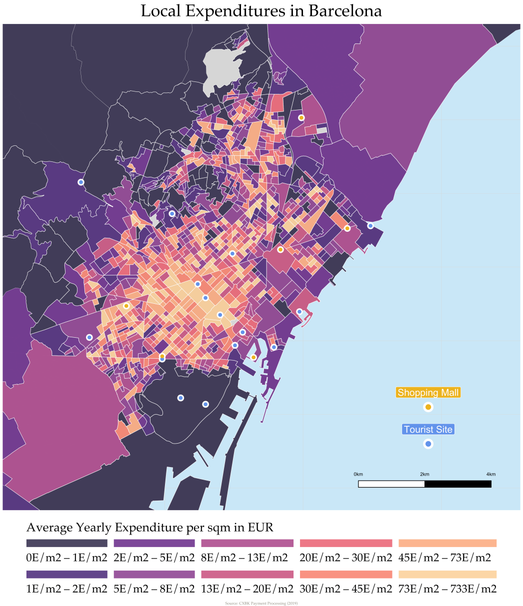
Income Distribution across Barcelona



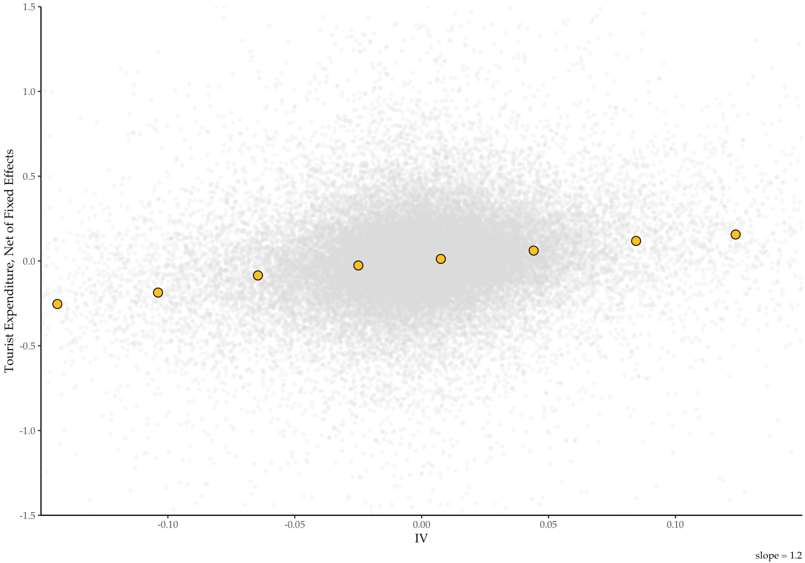
Mean Income

1039.61 – 1260.88	1421.98 – 1486.94	1585.91 – 1623.15	1705.59 – 1767.53	1956.66 – 2132.63
1260.88 – 1352.46	1486.94 – 1541.06	1623.15 – 1662.96	1767.53 – 1859.12	2132.63 – 2396.31
1352.46 – 1421.98	1541.06 – 1585.91	1662.96 – 1705.59	1859.12 – 1956.66	2396.31 – 11806.33

Local Spending Distribution across Barcelona



Shift Share: First Stage



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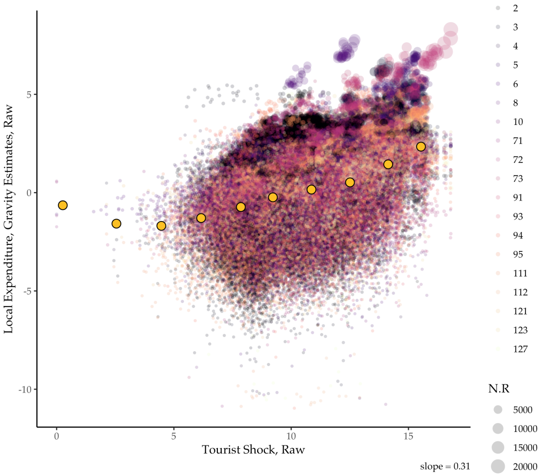
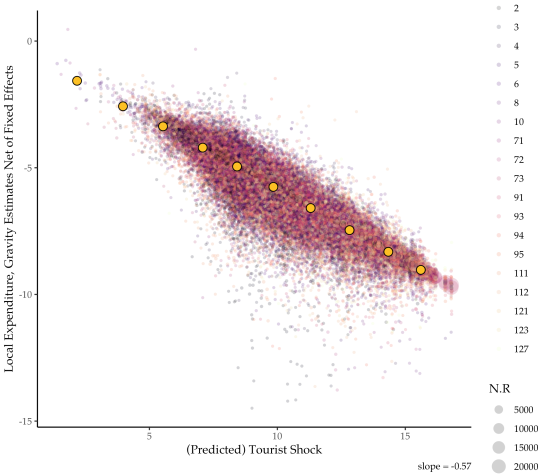
Price Regressions: Raw vs 2SLS





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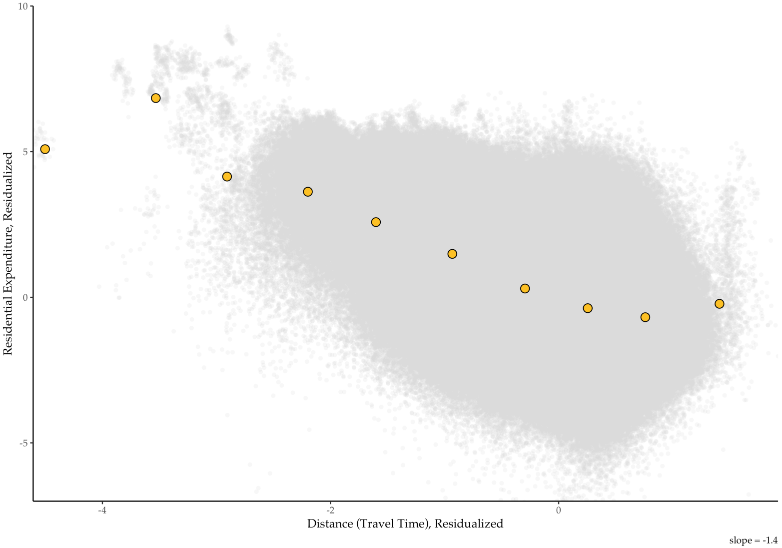
Fit of Gravity Specification



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Expenditure Gravity Regressions

Dependent Variables:	Bilateral Spending		log(Bilateral Spending+1)		log(Bilateral Spending)	
Model:	(1) Poisson	(2) Poisson	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Variables						
log(travel time)	-2.17***	-2.17***	-1.37***	-1.37***	-1.36***	-1.36***
	(0.003)	(0.003)	(0.0009)	(0.0009)	(0.001)	(0.001)
Fixed-effects						
Origin (CT)	✓		✓		✓	
Destination (CT)	✓		✓		✓	
Origin (CT)×YEARMONTH		✓		✓		✓
Destination (CT)×YEARMONTH		✓		✓		✓
Fit statistics						
Observations	43,204,320	43,125,480	43,204,320	43,204,320	6,566,622	6,566,622
Pseudo R^2	0.781	0.788	0.127	0.130	0.120	0.126

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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Is tourism good for the locals (on average)?

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

$$\frac{d \ln \bar{u}}{\partial \ln E^T} = \frac{\partial \ln \bar{v}}{\partial \ln E_i^T} - \frac{\partial \ln \bar{p}_s}{\partial \ln E_i^T}$$

- Results
  - Income elasticity: .04
  - Consumption Price Index elasticity: [.1,.175]
  - House Price elasticity: .06
  - Welfare elasticity: [-.1,-.04]
  - Average increase between February and July $\approx$ 50pc
  - Implies net welfare deterioration of 5pc

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Comparison with Household Budget Survey

COICOP (2D)	COICOP (2D)	Local	Spanish Tourists	Foreign Tourists	Total	Survey (INE)	Survey Adj (INE)
11	Food/Beverages	32.82 (24.72)	1.32 (5.04)	4.51 (5.10)	38.66	12.96	23.82
21	Alc Beverages	1.97 (1.48)	0.07 (0.28)	0.60 (0.68)	2.64	0.71	1.31
31	Clothing	11.58 (8.72)	1.94 (7.39)	12.00 (13.55)	25.51	3.39	6.23
41	Housing/Utilities	2.81 (2.12)	0.78 (3.00)	0.59 (0.67)	4.19	5.33	9.80
51	Furnishings	10.03 (7.55)	3.32 (12.67)	2.01 (2.27)	15.35	0.88	1.62
61	Health	10.76 (8.10)	1.94 (7.40)	1.82 (2.06)	14.52	2.24	4.12
71	Vehicle Purchase	3.14 (2.36)	0.18 (0.67)	0.32 (0.36)	3.63	3.78	6.95
72	Personal Transp	7.27 (5.47)	2.06 (7.89)	0.70 (0.79)	10.03	6.38	11.73
73	Transp Services	10.13 (7.63)	6.52 (24.90)	9.61 (10.85)	26.26	1.90	3.49
81	Communications	0.30 (0.23)	0.02 (0.09)	0.08 (0.09)	0.40	0.33	0.61
91	Audio-visual	5.06 (3.81)	0.57 (2.17)	1.78 (2.01)	7.40	0.58	1.07
93	Recreational	2.62 (1.97)	0.27 (1.03)	1.21 (1.37)	4.09	1.43	2.63
94	Cultural Services	4.29 (3.23)	0.62 (2.38)	2.79 (3.15)	7.70	0.57	1.05
95	Books, etc	1.64 (1.23)	0.22 (0.85)	0.53 (0.60)	2.39	1.30	2.39
101	Education	1.11 (0.84)	0.10 (0.39)	0.61 (0.69)	1.82	0.77	1.41
111	Restaurants	17.73(13.35)	3.79 (14.46)	19.04 (21.50)	40.56	7.83	14.39
112	Hotels	1.13 (0.85)	1.49 (5.69)	23.12 (26.11)	25.75	1.21	2.22
121	Personal Care	4.84 (3.64)	0.32 (1.23)	0.97 (1.10)	6.14	2.53	4.65
123	Other	2.49 (1.88)	0.36 (1.37)	5.69 (6.42)	8.54	0.32	0.59
Total		131.72 (100)	25.88 (100)	87.97 (100)	245.58	54.4	100

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Hat Algebra

- Market Clearing Condition

$$\hat{y}_{is} = \pi_{is}^{local} \sum_{n=1}^{N} \left(\pi_{is}^{n} \hat{s}_{nis} \hat{v}_n\right) + \pi_{is}^{group} \sum_{g=1}^{G} \left(\pi_{is}^{g} \hat{s}_{gis} \hat{E}_g^T\right)$$

- Labor Market Clearing

$$\sum_s \frac{\beta_s y_{is}}{\sum_{s'} \beta_s y_{is'}} \hat{y}_{is} = \sum_{n=1}^{N} \frac{w_i \ell_{ni}}{\sum_{n'=1}^{N} w_i \ell_{n'i}} \left(\hat{w}_{ni}\right)^{\theta} \hat{T}_n \hat{W}_n^{1-\theta}$$

- Disposable Income

$$\hat{v}_n = \sum_{i=1}^{N} \frac{l_{ni} w_i}{\sum_{i'=1}^{N} l_{ni'} w_{i'}} \left(\hat{w}_{ni}\right)^{\theta} \hat{T}_n \hat{W}_n^{1-\theta}$$

Parameterization

Parameter	Value	Comment
β_s	$0.65\ \forall s$	labor share of income
σ_s	$4\ \forall s$	elasticity of substitution (within sectors)
η	1.5	elasticity of substitution (between sectors)
θ	1.5	labor dispersion $(1-\epsilon)$
γ	$[0, 0, 0, 0]$	consumption spillovers

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Data Requirements

Data	Description	Comment
l_{ni}	Commuting Flows	Lunch Expenditures
x_{nis}	Base Local Expenditures	
x_{gis}	Base Tourist Expenditures	
$\hat{E}_i^T$	Change in Tourist Expenditures	Difference from Jan to July
v_n	Worker Incomes	

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Roy's Identity for Labor Supply

- Income maximization problem:

$$v_n = \max_{\{\ell_i\}} \sum_{i=1}^{N} w_i \ell_i \qquad \text{s.t.} \qquad H_n(\boldsymbol{\ell}_n) = T_n$$

- Maximand is the income function $\boldsymbol{y}(\boldsymbol{w}_n, T_n)$ and envelope theorem implies,

$$\frac{\partial y(\cdot)}{\partial w_i} = \ell_i$$

- Dual is cost minimization problem, where minimand is $\boldsymbol{h}\left(\boldsymbol{w}_n, \bar{Y}\right)$

- Differentiating we obtain,

$$\frac{\partial y(\cdot)}{\partial w_i} = -\frac{\frac{\partial h(\boldsymbol{w}_n, y(\boldsymbol{w}_n, T_n))}{\partial w_i}}{\frac{\partial h(\boldsymbol{w}_n, y(\boldsymbol{w}_n, T_n))}{\partial v}} = \ell_i$$

Derivation of Welfare Formula

- Assuming both homothetic demand and a homothetic income maximization problem allows us to write the indirect utility function as,

$$u_n = \frac{T_n J(\boldsymbol{w}_n)}{G(\boldsymbol{p}_n)}$$

- Totally differentiating,

$$\frac{\mathrm{d}u_n}{u_n} = \sum_{i=1}^{N} \frac{1}{J(\boldsymbol{w}_n)} \frac{\partial (J(\boldsymbol{w}_n))}{\partial w_i} w_i \frac{\mathrm{d}w_i}{w_i} + \sum_{i=1}^{N} G(\boldsymbol{p}_n) \frac{\partial (1/G(\boldsymbol{p}_n))}{\partial p_{ni}} p_{ni} \frac{\mathrm{d}p_{ni}}{p_{ni}}$$

- Applying Roy's identity for the income maximization and consumption problem from above,

$$\frac{\mathrm{d}u_n}{u_n} = \sum_{i=1}^{N} \frac{\ell_i}{v_n} w_i \frac{\mathrm{d}w_i}{w_i} - \sum_{i=1}^{N} \frac{q_{ni}}{v_n} p_{ni} \frac{\mathrm{d}p_{ni}}{p_{ni}}$$

Price Regressions: Group Estimates

Dependent Variables:	δ^{R}_{ist}	$\delta^{T.Dom}_{ist}$	$\delta^{T.For}_{ist}$	δ^{R}_{ist}	$\delta^{T.Dom}_{ist}$	$\delta^{T.For}_{ist}$
	OLS			IV - Ref: 2017 Average		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
$\ln E^{T}_{it}$	0.091***	0.485***	0.454***	-0.576***	-0.277***	0.029
	(0.003)	(0.005)	(0.004)	(0.034)	(0.077)	(0.056)
Fixed-effects						
Month-Year×Sector (480)	✓	✓	✓	✓	✓	✓
Location×Sector (21,920)	✓	✓	✓	✓	✓	✓
Location×Sector×Year (43,840)	✓	✓	✓	✓	✓	✓
Location×Sector×Month (263,040)	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	526,080	526,080	526,080	526,080	526,080	526,080
Adjusted R^2	0.994	0.991	0.994	0.993	0.99	0.993

Normal standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

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