

Urban Welfare: Tourism in Barcelona

Treb Allen

Dartmouth & NBER

Simon Fuchs

*FRB Atlanta**

Sharat Ganapati

Georgetown & NBER

Rocio Madera

SMU & CESifo

Alberto Graziano

Judit Montoriol-Garriga

*CaixaBank Research**

Boston University

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- + “Lets the data speak”; relaxes parametric assumptions (e.g. Frechet).
- No insight into aggregate & welfare effects; ignores GE spatial linkages.

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- Option **2**: Model based framework: e.g.:

$$\hat{y}_{it} = \sum_{j=1}^J \pi_{ij} \times \hat{\mathbf{shock}}_{jt} \times \hat{y}_{jt}^{\theta}$$

- + Incorporates aggregate & welfare effects + GE spatial linkages.
 - Relies on model assumptions / simplifications; results can be opaque.

This Paper: Option 3

- Regression based approach, designed by theory.
 - **Welfare effects** of (local) shocks **with minimal modeling assumptions**.
 - “Lets the data speak”: **Incorporates GE** spatial linkages **into empirical framework**.

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 2. Perturbation to market clearing → GE spatial linkages

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 - Rich new data on expenditure and income spatial patterns
 - Causal (shift-share) identification from variation in tourist timing from RoW
- Show that it outperforms options 1 & 2.

Literature and Contribution

First-Order Impact of Price Shocks

- Deaton (1989), Kim & Vogel (2020), Atkin *et al.* (2018), Baqaee & Burstein (2022)

Small shocks in general equilibrium

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

Impact of Tourism

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

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 *et al.* (2020), Davis *et al.* (2019), Agarwal *et al.* (2017), Miyauchi *et al.* (2021)

Outline of Talk

A General Methodology for (small) Urban Shocks

Tourism in Barcelona

Empirical Strategy and Identification

Is Tourism Good for Locals?

Comparison with a Quantitative GE Model

Conclusion

Setup

Setup Details

- A city is a set of $\{1, \dots, N\} \equiv \mathcal{N}$ **blocks**.
- Each $n \in \mathcal{N}$ inhabited by **representative resident**
 - with homothetic preferences.
- Each $i \in \mathcal{N}$ inhabited by **representative firm** producing **differentiated variety**
 - with CRS technology.
- Residents Blocks are separated by (*iceberg*) *commuting and trade costs*.
- Tourists reside in RoW $i = 0$, produce own (numeraire) variety.

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Question

Impact of a (foreign) demand shock $E^T \equiv \{E_1^T, \dots, E_N^T\}$ on residents $\{1, \dots, N\}$ welfare?

Residents

Residents

- Representative resident n consumes/commutes to solve:

$$\max_{\{c_{ni}, l_{ni}\}} u_n \left(\{c_{ni}\}_{i \in \{0, \mathcal{N}\}} \right)$$

s.t. to budget & labor constraints:

$$\sum_{i \in \{0, \mathcal{N}\}} p_{ni} c_{ni} \leq \sum_{i \in \mathcal{N}} w_{ni} l_{ni}$$

$$H_n \left(\{l_{ni}\}_{i \in \mathcal{N}} \right) \leq T_n$$

increasing & weakly convex fixed labor endowment

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increasing & weakly convex fixed labor endowment

- Homothetic demand $\implies u_n = v_n / G(\mathbf{p}_n)$, where income v_n solves:

$$v_n \equiv \max_{\{l_{ni}\}} \sum_{j \in \mathcal{N}} w_j l_{nj}$$

s.t. the labor constraint.

Insight 1: An analytical expression for welfare impact of (small) shocks

Q: What is the first order impact of a change in prices and/or wages on the welfare of residents in n ?

- Optimization gives indirect utility $u_n = \frac{T_n \overset{\text{Wage aggregator}}{J(\mathbf{w}_n)}}{\underset{\text{Price aggregator}}{G(\mathbf{p}_n)}}$
- Then envelope theorem yields

$$\mathbf{d} \ln \text{utility}_n = \underbrace{\sum_i \mathbf{c}ommuting_{n \rightarrow i} \times \partial \ln \mathbf{w}ages_i}_{\Delta \text{Spatial Income}} - \underbrace{\sum_i \mathbf{s}pending_{n \rightarrow i} \times \partial \ln \mathbf{p}rices_i}_{\Delta \text{Spatial Price Index}} \quad (1)$$

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- Extends the insights of e.g. Houthakker (1952), Domar (1961), Hulten (1978), Deaton (1989), Porto (2006) to an urban setting with commuting.

Production and Market Clearing

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- Representative firm in location $i \in \mathcal{N}$ combines labor, capital and a specific factor to produce its differentiated variety, with share of θ_i^l (θ^k) of income accruing to labor (capital).

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 - Firm income is equal to total sales:

$$y_i = p_i q_i = \sum_{n \in \mathcal{N}} s_{in} v_n + s_i E^T,$$

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- Fraction θ_i^l of firm income accrues to labor:

$$\sum_{n \in \mathcal{N}} w_{in} l_{ni} = \theta_i^l \left(\sum_{n \in \mathcal{N}} s_{in} v_n + s_i E^T \right)$$

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- Holding labor & exp. shares fixed and perturbing the market clearing conditions:

$$\partial \ln \mathbf{p} = \beta (\mathbf{M} d \ln \mathbf{w} + \mathbf{D}^T \partial \ln \mathbf{E}^T)$$

$$\partial \ln \mathbf{w} = \beta (\mathbf{I} - \mathbf{M})^{-1} \mathbf{D}^T \partial \ln \mathbf{E}^T$$

where $\beta \equiv 1 - \theta^k$ and:

$$\mathbf{M} \equiv (\mathbf{D}_y)^{-1} \mathbf{S} \mathbf{D}_v \mathbf{C}; \quad \mathbf{S} \equiv [s_{in}]; \quad \mathbf{C} \equiv [c_{nj}];$$

$$\mathbf{D}_y \equiv \text{diag}(y_i); \quad \mathbf{D}_v \equiv \text{diag}(v_n); \quad \mathbf{D}_T \equiv \text{diag}\left(\frac{s_i E^T}{y_i}\right)$$

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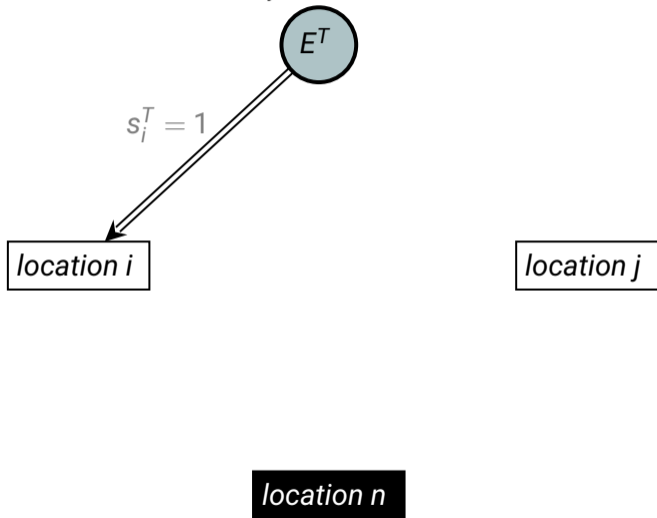
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! Short-run GE response to *local* shocks in *static* framework.

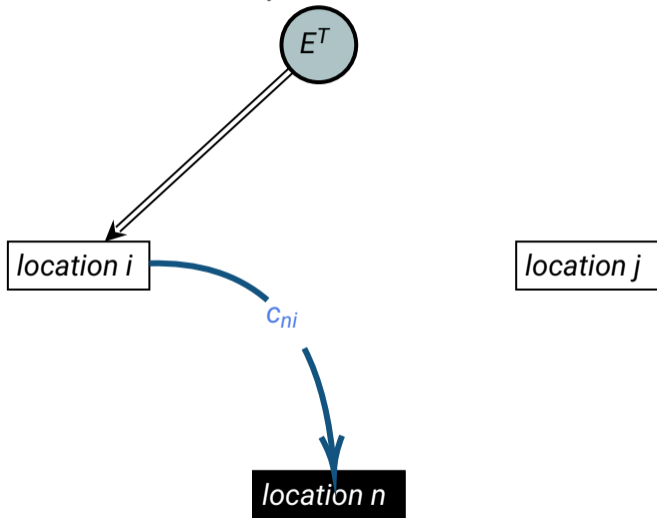
Intuition for the GE propagation

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



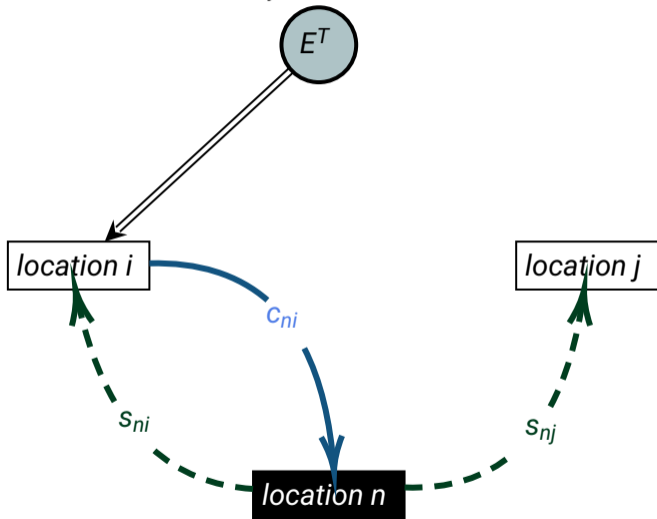
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Consider external **demand shock** E^T to a city \rightarrow **Income Shock**



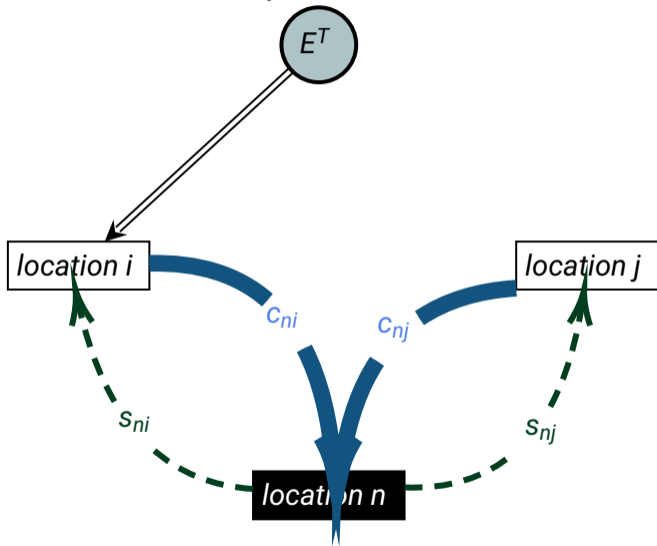
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Consider external **demand shock** E^T to a city \rightarrow **Income Shock** \rightarrow **Demand**



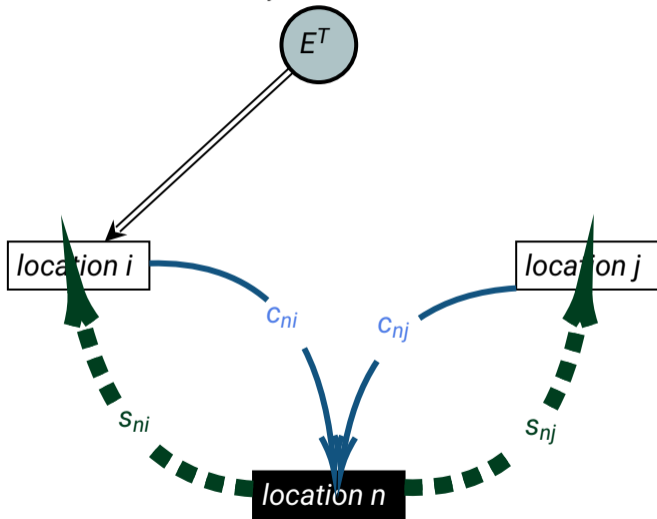
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Insight 2: Analytical expressions for GE propagation of shocks, ctd.

- Solving the system and using a Neumann series expansion:

$$\begin{aligned} \frac{\partial \ln p_i}{\partial \ln E^T} &= \underbrace{\beta (1 + [M_{ii}] + [M_{ii}^2] + \dots)}_{\text{GE HTE of own shock}} \left(\frac{s_i E^T}{y_i} \right) \\ &+ \underbrace{\beta \sum_{j \neq i} ([M_{ij}] + [M_{ij}^2] + \dots)}_{\text{GE spillovers from shocks elsewhere}} \left(\frac{s_j E^T}{y_j} \right) \end{aligned} \quad (2)$$

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- And similarly for residential incomes:

$$\frac{\partial \ln v_n}{\partial \ln E^T} = \beta \sum_{j \in \mathcal{N}} c_{nj} \sum_{k \in \mathcal{N}} ([M_{jk}^0] + [M_{jk}] + [M_{jk}^2] + \dots) \left(\frac{s_k E^T}{y_k} \right) \quad (3)$$

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- *Question:* Welfare impact on residents of a demand shock in a spatial network?

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- Proposed framework provides analytical expressions for:
 - Resident welfare (equation 1)
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- Evaluating the welfare effects of an urban shock requires:
 - Consumption share data $\mathbf{S} \equiv \{\mathbf{s}_{ni}\}_{n=1,i=1}^{N,N}$
 - Income share data $\mathbf{C} \equiv \{\mathbf{c}_{ni}\}_{n=1,i=1}^{N,N}$
 - Estimates of key elasticities: $\{\partial \ln p_i, \partial \ln v_n\}_{i=1}^N$ to an exogenous shock $\partial \ln E^T$ (next)

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(Within-year) welfare impact of tourism spending on locals?

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

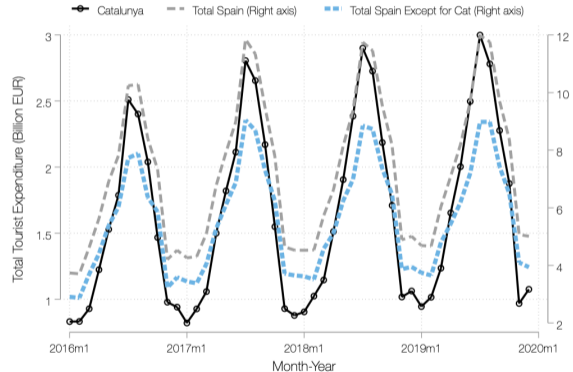
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- Contentious



New Generation of High Resolution Urban Datasets

- Working closely with Caixabank, largest Spanish bank based in Barcelona
- First paper to combine:
 1. High resolution bilateral expenditure data.
 2. High resolution residential income data.
 3. High resolution commuting data.

High Resolution Data on Urban Consumption & Income Networks

Consumption Shares

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

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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
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Housing prices and rental rates

- Idealista ("Spanish Zillow")
- Monthly frequency for neighborhoods (more aggregated than census blocks)

Two Stylized Facts Towards Welfare Analysis

FACT 1: Tourist spending varies across space and time

→ Identification strategy for elasticities

FACT 2: Locals' spending and income spatially determined by residence

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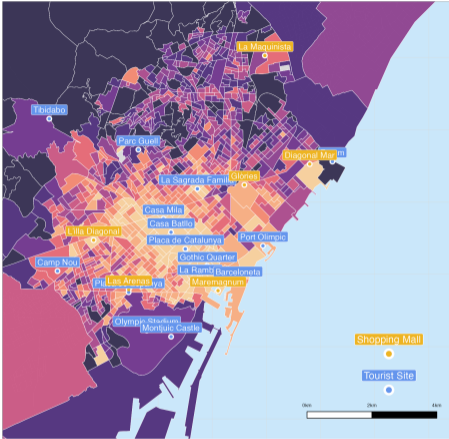
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Fact 1A: Tourist spending varies across space

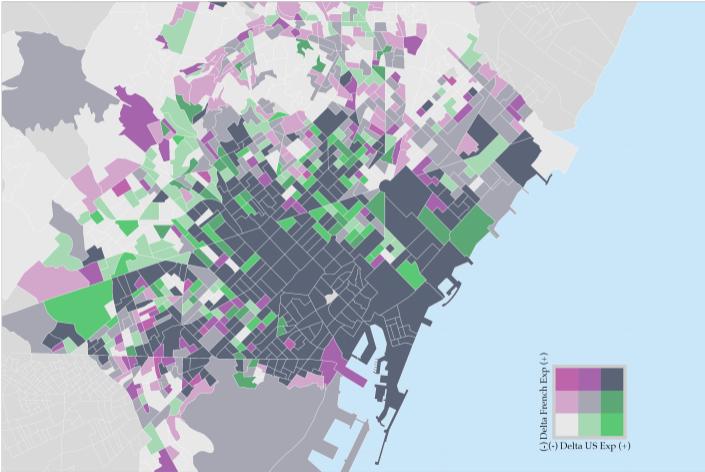
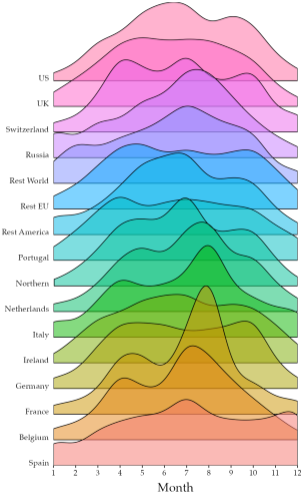


Average (yearly) expenditure per sqm by tourists.



FACT 1B: Tourism varies across time within the city

Monthly Expenditure Shares



Two Stylized Facts Towards Welfare Analysis

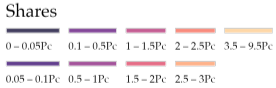
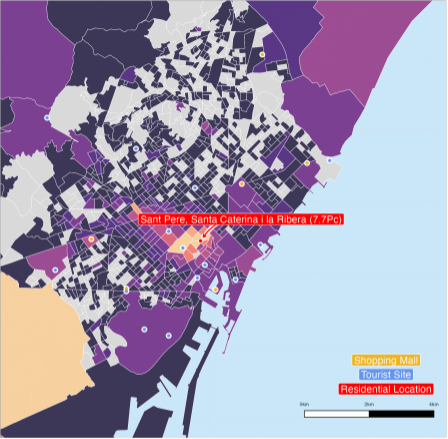
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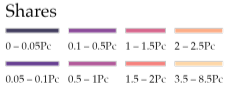
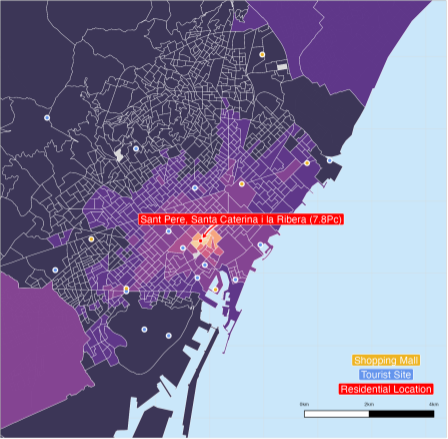
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Fact 2: Locals spending and income patterns vary by residence

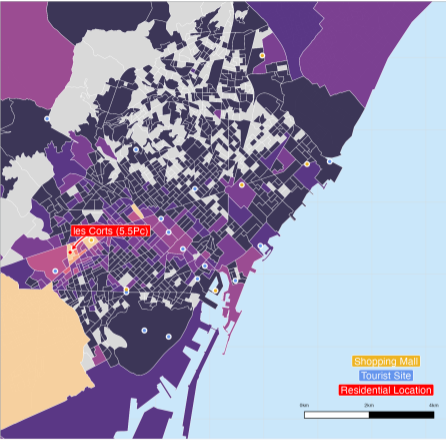


Cross-Sec. Local Spending Cross-Sec. Income

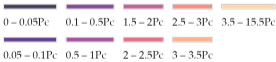


Exp Gravity Commuting Gravity

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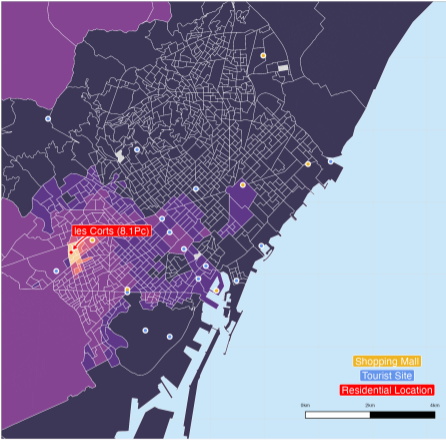


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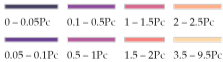


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From **Theory** to Estimation

- Recall from equation (1) we have the following welfare expression:

$$d \ln u_n = \partial \ln v_n - \sum_{j \in \mathcal{N}} s_{nj} \partial \ln p_j$$

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- Recall from equation (1) we have the following welfare expression:

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- From equations (2) and (3) we have the changes in prices and incomes:

$$\partial \ln p_i = \beta \sum_{j \in \mathcal{N}} \sum_{k \geq 0} M_{ij}^k \left(\frac{E_j^T}{y_j} \right) \partial \ln E_j^T$$

$$\partial \ln v_n = \beta \sum_{i \in \mathcal{N}} c_{ni} \sum_{j \in \mathcal{N}} \sum_{k \geq 0} M_{ij}^k \left(\frac{E_j^T}{y_j} \right) \partial \ln E_j^T$$

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- Recall from equation (1) we have the following welfare expression:

$$d \ln u_n = \partial \ln v_n - \sum_{j \in \mathcal{N}} s_{jn} \partial \ln p_j$$

- Equations (2) and (3) in regression form:

$$\ln p_{it} = \beta \sum_{j \in \mathcal{N}} \sum_{k \geq 0} M_{ij}^k \left(\frac{E_{j0}^T}{y_{it}} \right) \ln E_{jt}^T + \delta_i + \delta_t + \varepsilon_{it}$$

$$\ln v_{nt} = \beta \sum_{i \in \mathcal{N}} c_{ni} \sum_{j \in \mathcal{N}} \sum_{k \geq 0} M_{ij}^k \left(\frac{E_{j0}^T}{y_{j0}} \right) \ln E_{jt}^T + \delta_n + \delta_t + \varepsilon_{nt}$$

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→ *Solution*: "shift-share" IV relying on variation in tourist preferences across origins & timing of visitors (from Fact 1B)

1. Recovering amenity-adjusted prices

- From CES preferences, derive gravity regression, estimate by PPML

- $\ln \delta_{it}$ is the destination fixed effect of a gravity regression:

$$\ln X_{nit} = \ln \delta_{nt} + \ln \delta_{it} + (1 - \sigma_t) \ln \tau_{nit} + \varepsilon_{nit}$$

- τ_{nit} is the iceberg friction (calculated from travel time, origin income, and average bilateral expenditure)

1. Recovering amenity-adjusted prices

- From CES preferences, derive gravity regression, estimate by PPML

- $\ln \delta_{it}$ is the destination fixed effect of a gravity regression:

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- Amenity-adjusted prices: $\ln p_{it} = (1/(1 - \hat{\sigma}_t)) \times \ln \hat{\delta}_{it}$

2. Identification: Shift-Share IV from Het Tourist Pref

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- Shifts E_{gt}^T from changes in total tourist expenditure (elsewhere)

Estimation & Results

Effect of tourism on prices

- Average treatment effect:

$$\ln p_{it} = \beta_1 \ln E_{it}^T + \delta_i + \delta_t + \varepsilon_{it}$$

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- With own & others GE linkages:

$$\begin{aligned} \ln p_{it} = & \beta_1 \ln E_{it}^T + \underbrace{\beta_2 (1 + [M_{ii}] + \dots) \left(\frac{E_{i0}^T}{y_{i0}} \right)}_{\text{GE HTE of own shock}} \ln E_{it}^T \\ & + \underbrace{\beta_3 \sum_{j \neq i} ([M_{ij}] + \dots) \left(\frac{E_{j0}^T}{y_{j0}} \right)}_{\text{GE spillovers from shocks elsewhere}} \ln E_{jt}^T + \delta_i + \delta_t + \varepsilon_{it} \end{aligned}$$

Effect of tourism on prices

DEPENDENT VARIABLE: LOG LOCAL PRICE (AMENITY-ADJUSTED)

**ATE:
No Spatial Spillovers**

Local Tourist Spending 0.0536*
(0.0292)

Tourist Spending Everywhere (GE)

GE Locally

Spillovers from Elsewhere

Fixed-effects

Census Tract Yes

Year-Month Yes

N 25,379

Within R² 0.01481

*Driscoll-Kraay (L=2) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Effect of tourism on prices

DEPENDENT VARIABLE: LOG LOCAL PRICE (AMENITY-ADJUSTED)

	ATE: No Spatial Spillovers	GE (exact sum): All Spatial Spillovers
Local Tourist Spending	0.0536* (0.0292)	-0.0357 (0.0258)
Tourist Spending Everywhere (GE)		0.3449*** (0.0607)
GE <i>Locally</i>		
Spillovers from <i>Elsewhere</i>		
<i>Fixed-effects</i>		
Census Tract	Yes	Yes
Year-Month	Yes	Yes
N	25,379	25,379
Within R ²	0.01481	0.03878

*Driscoll-Kraay (L=2) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Effect of tourism on prices

DEPENDENT VARIABLE: LOG LOCAL PRICE (AMENITY-ADJUSTED)

	ATE: No Spatial Spillovers	GE (exact sum): All Spatial Spillovers	GE (exact sum): Own/Else Spillovers
Local Tourist Spending	0.0536* (0.0292)	-0.0357 (0.0258)	-0.0357 (0.0263)
Tourist Spending Everywhere (GE)		0.3449*** (0.0607)	
GE <i>Locally</i>			0.3306*** (0.0558)
Spillovers from <i>Elsewhere</i>			0.4184*** (0.1463)
<i>Fixed-effects</i>			
Census Tract	Yes	Yes	Yes
Year-Month	Yes	Yes	Yes
N	25,379	25,379	25,379
Within R ²	0.01481	0.03878	0.04174

*Driscoll-Kraay (L=2) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Inside GE Propagation

Prices

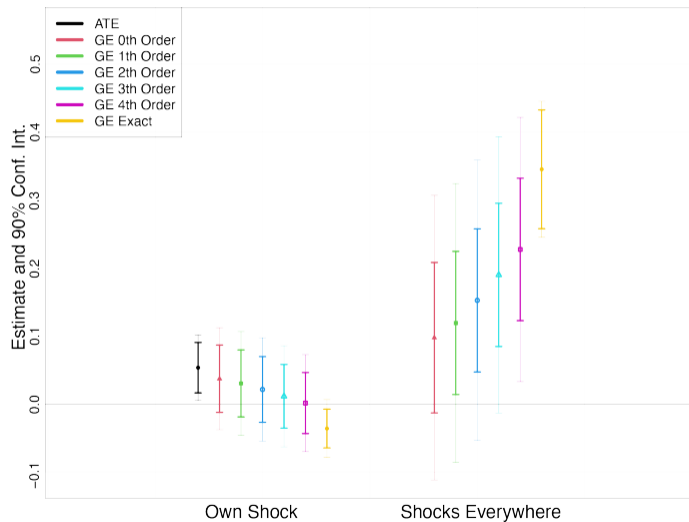
- Consider different degree approximations to GE linkages
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Inside GE Propagation

Prices

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- Thinner C.I.: Driskoll-Kraay S.E.
- Thicker C.I.: Robust S.E.



Effect of tourism on incomes

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Effect of tourism on incomes

DEPENDENT VARIABLE: LOG LOCAL EARNINGS

	ATE: No Spatial Spillovers	GE: All Spatial Spillovers	GE: Own/Else Spillovers
Local Tourist Spending	0.0109 (0.0065)	0.0059 (0.0045)	0.0059 (0.0044)
Tourist Spending Everywhere (GE)		0.3040** (0.1464)	
GE <i>Locally</i>			0.3040** (0.1462)
Spillovers from <i>Elsewhere</i>			0.3032 (0.2453)
<hr/>			
<i>Fixed-effects</i>			
Census Tract	Yes	Yes	Yes
Year-Month	Yes	Yes	Yes
<hr/>			
N	25,379	25,379	25,379
Within R ²	0.00025	0.00116	0.00116

*Driscoll-Kraay (L=2) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Inside GE Propagation

Incomes

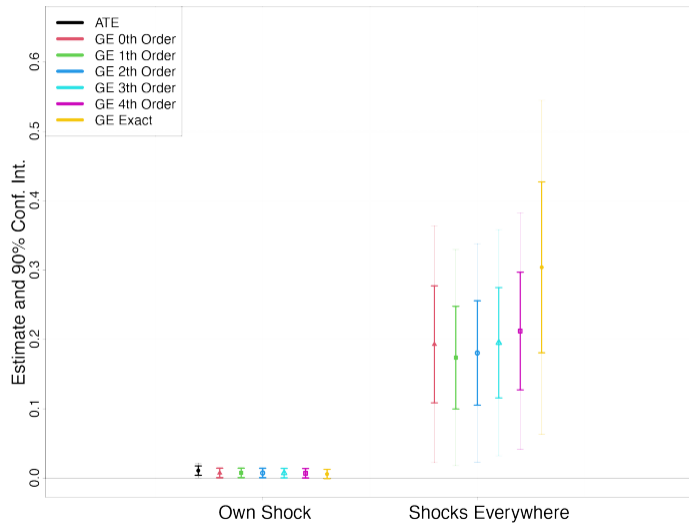
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A General Methodology for (small) Urban Shocks

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Empirical Strategy and Identification

Is Tourism Good for Locals?

Comparison with a Quantitative GE Model

Conclusion

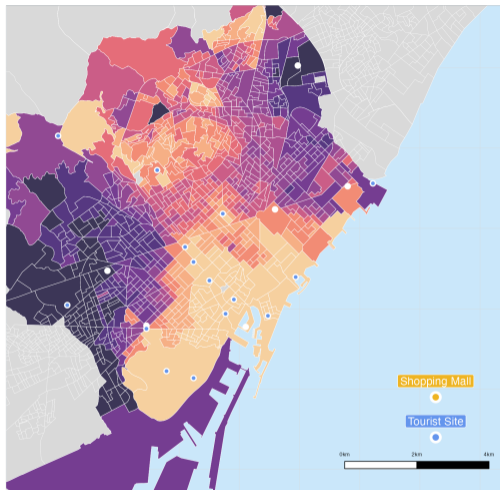
Is tourism *good* for locals?

- Welfare Formula

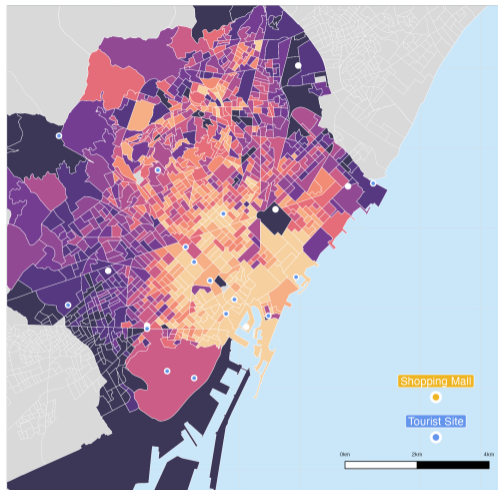
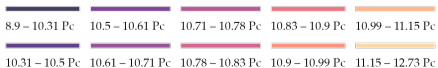
$$d \ln u_n = \frac{\partial \ln v_n}{\partial \ln E_i^T} \times d \ln E_i^T - \sum_i s_{ni} \times \frac{\partial \ln p_i}{\partial \ln E_i^T} \times d \ln E_i^T$$

- s_{ni} use baseline averages in 2017
- Predict income and price changes from January to July using our data and IV

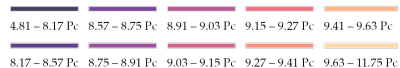
Income (Panel A) and Price Effects (Panel B) - GE



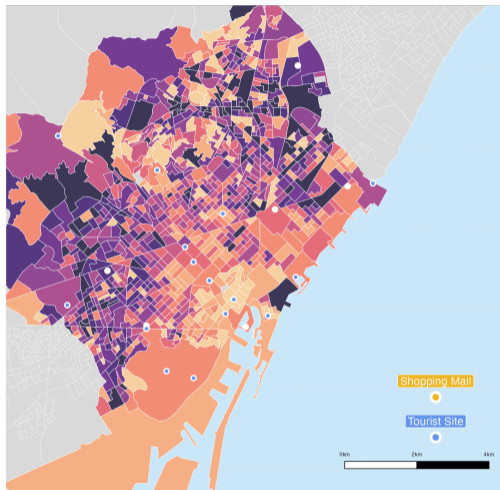
Change in Income (GE)



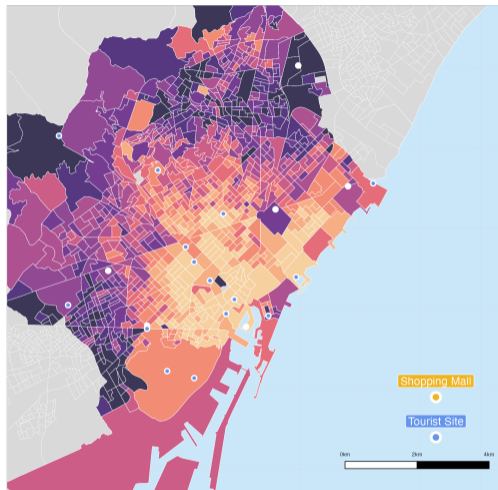
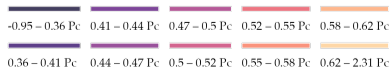
Change in Price Index (GE)



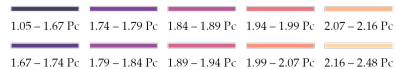
Income (Panel A) and Price Effects (Panel B) - ATE



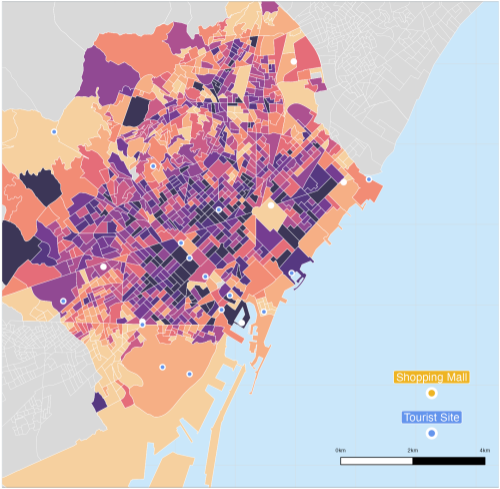
Change in Income (ATE)



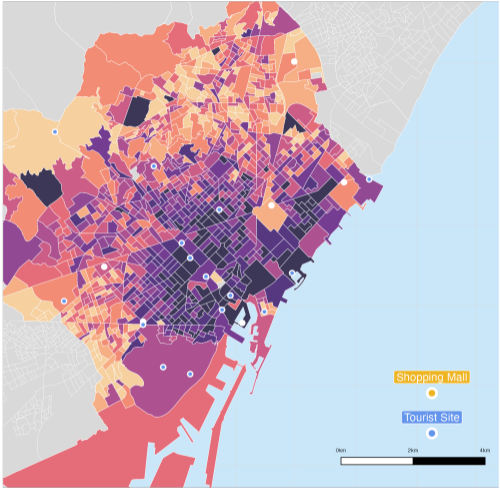
Change in Price Index (ATE)



Welfare Effects: With and without GE spillovers



Change in Welfare (GE)



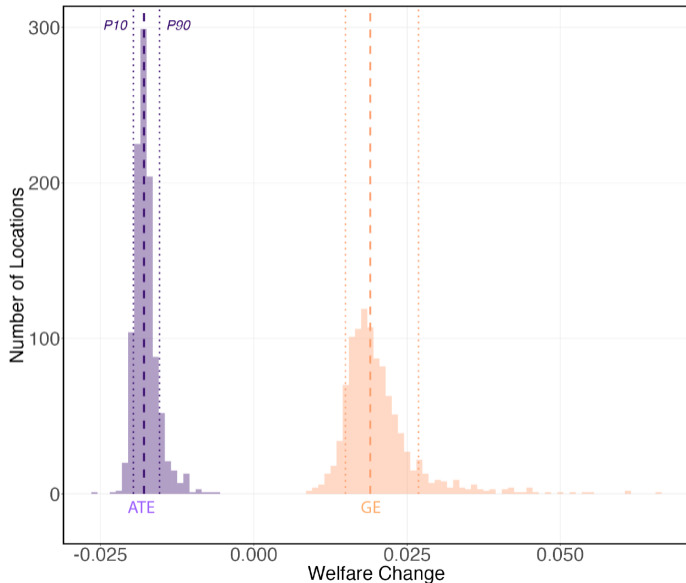
Change in Welfare (ATE)

Welfare Effects: With and without GE spillovers

Average resident's welfare impact of tourists:

- With GE: 1.8%
- Without GE: -1.4%

⇒ Ignoring GE spillovers understates welfare benefits



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How does our approach compare to a quantitative GE model?

- Consider a standard urban “quantitative” model with:
 - Cobb-Douglas nest of housing and a CES composite of tradables.
 - Frechet distribution of firm & resident productivities
 - Cobb-Douglas production functions.

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- With structural elasticities calibrated to match:
 - Income responses to tourism (commuting elasticity 4.65)
 - Expenditure responses to prices (demand elasticity ~ 9)
 - Housing share (0.3) adjusted to account for spatial variation in home-ownership rates
 - Observed capital (0.43), labor (0.35), and specific factor shares (0.22)

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- Delivers the same GE market clearing conditions as above.

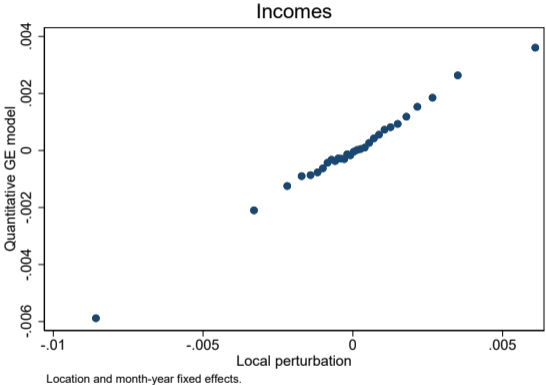
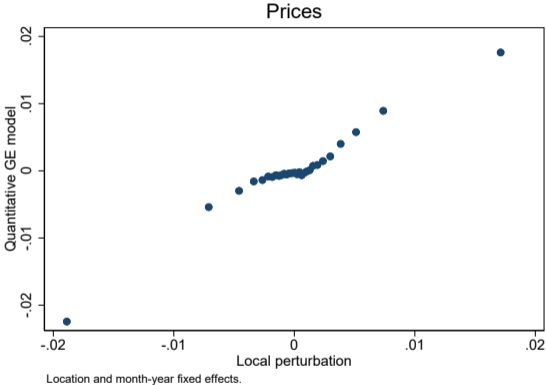
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- Delivers the same GE market clearing conditions as above.
- But can now solve for exact (non short-run, non-local) changes in prices and incomes.
- *Question*: Does this quantitative GE model better explain the data?

Comparison to full quantitative model: Predictions are very similar



Comparison to full quantitative model: Effect of tourism on prices

DEPENDENT VARIABLE: LOG LOCAL PRICE (AMENITY-ADJUSTED)

	Local perturbation	Quantitative GE model	Both
Local perturbation	1.000*** (0.267)		1.104** (0.418)
Quantitative GE model		0.149 (0.379)	-0.117 (0.405)
<i>Fixed-effects</i>			
Census Tract	Yes	Yes	Yes
Year-Month	Yes	Yes	Yes
N	25,377	25,377	25,377
Within R ²	0.0388	0.0032	0.0403

*Driscoll-Kraay (L=2) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Comparison to full quantitative model: Effect of tourism on incomes

PANEL B: LOG LOCAL EARNINGS

	Local perturbation	Quantitative GE model	Both
Local perturbation	1.000** (0.450)		0.685 (0.424)
Quantitative GE model		1.000* (0.501)	0.656 (0.498)
<i>Fixed-effects</i>			
Census Tract	Yes	Yes	Yes
Year-Month	Yes	Yes	Yes
N	25,377	25,377	25,377
Within R ²	0.0012	0.0011	0.0015

*Driscoll-Kraay (L=2) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

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 - Identification based on timing/preferences of different tourist groups

- Results suggest:
 - Our method captures important GE variation missed by traditional approaches, with important welfare implications.
 - Quantitative GE approach add little additional insight
 - Substantial variation in welfare effect of tourism, depending on where you live.

Theory Appendix

Commuting Implied Exposure Derivation

- Disposable income is given by

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

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

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

- Impact of tourist expenditure shock,

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

Shift-Share Instrument: Derivations

- Representative tourist for group g has preferences,

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

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

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

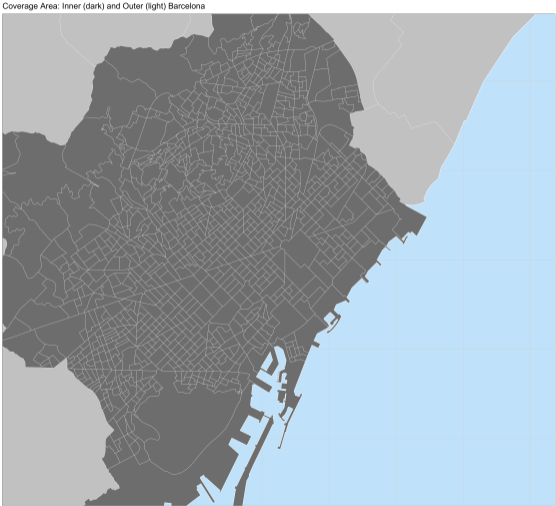
- Taking it to the data,

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

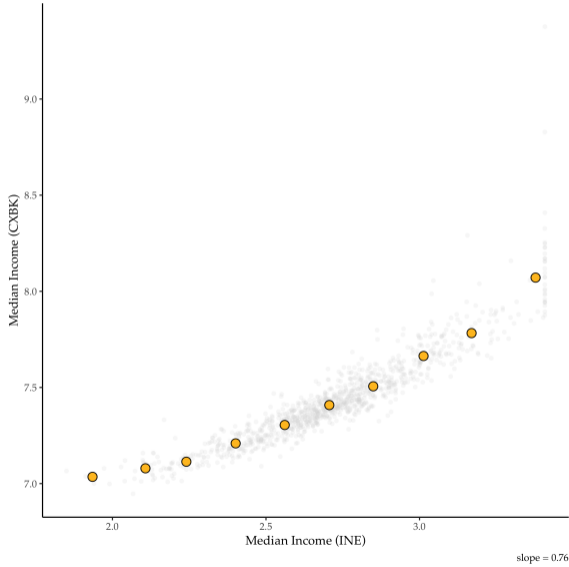
- where $\epsilon_{imt}^T = \sum_g s_{gi} db_{gi} + \sum_g s_{gi} dp_i$

Data Appendix

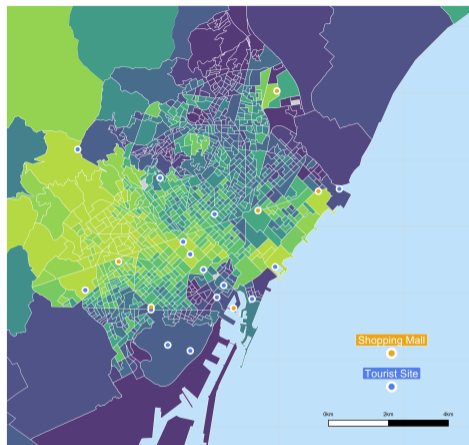
Sample of Locations



Income Data: Comparison with Administrative Data



Income Distribution across Barcelona

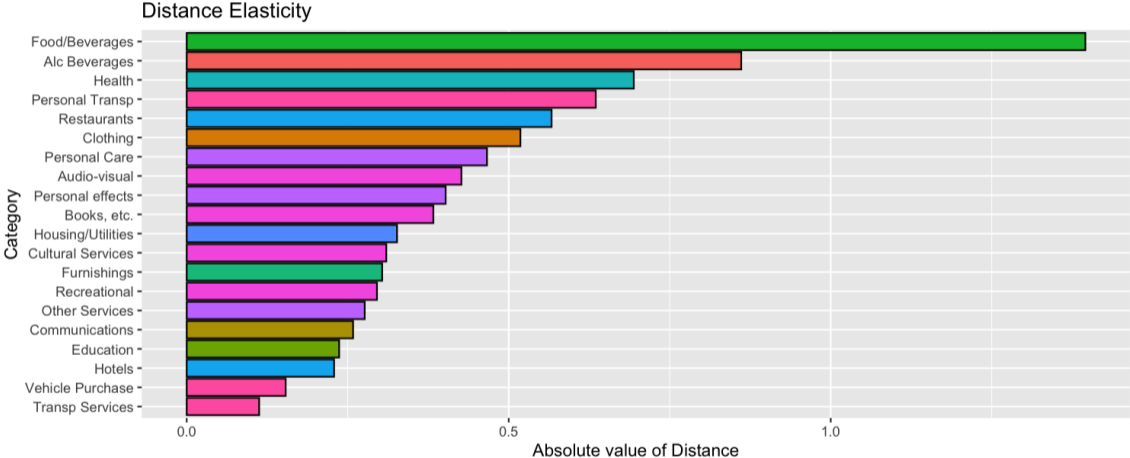


Mean Income



Empirical Analysis Appendix

Distance Coefficient for Gravity by Sector



Source: CXBK Payment Processing (2019)

Commuting Gravity Estimates

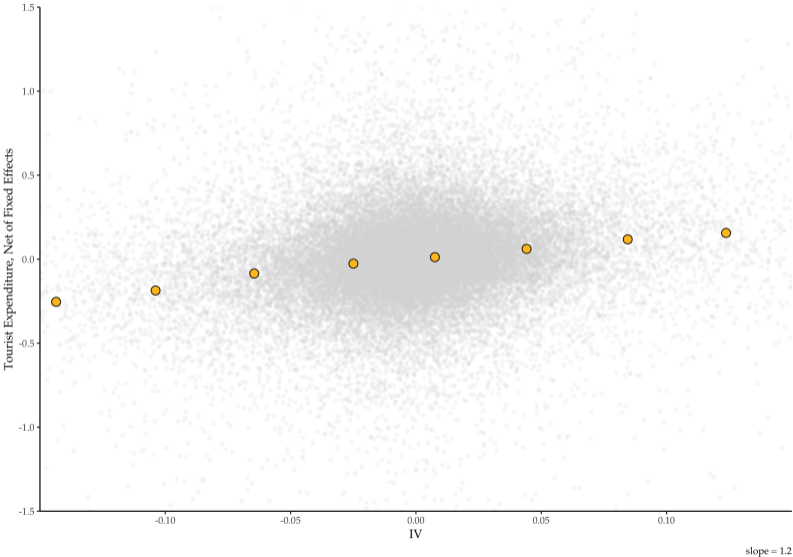
Dependent Variables: commuters log(commuters+1) log(commuters) transactions log(transactions+1) log(transactions)						
	Cell Phone			Lunchtime		
Model:	(1) Poisson	(2) OLS	(3) OLS	(4) Poisson	(5) OLS	(6) OLS
<i>Variables</i>						
ldist	-4.48*** (0.107)	-1.51*** (0.037)	-1.17*** (0.054)	-1.53*** (0.028)	-0.134*** (0.002)	-0.411*** (0.012)
<i>Fixed-effects</i>						
Origin	✓	✓	✓			
Destination	✓	✓	✓			
Origin (CT)				✓	✓	✓
Destination (CT)				✓	✓	✓
<i>Fit statistics</i>						
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*

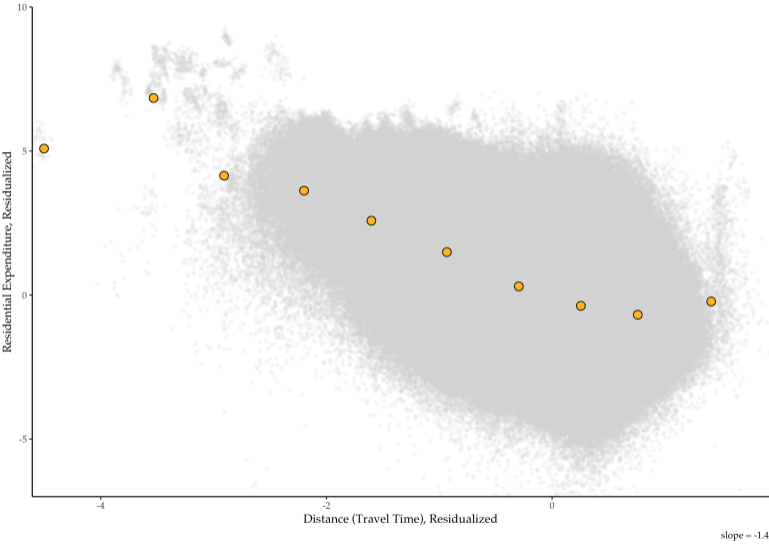
Impact of tourism on housing

Dependent Variable: log Housing prices		
	ATE: Housing Price	ATE: Rent
Own Tourist Shock	0.095 (0.0341)**	0.066 (0.024)**
<i>Fixed Effects</i>		
Census Tract	Yes	Yes
N	1,728	1,718
Within R^2	0.004	0.001

Shift Share: First Stage



Fit of Gravity Specification



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
<i>Variables</i>						
log(travel time)	-2.17*** (0.003)	-2.17*** (0.003)	-1.37*** (0.0009)	-1.37*** (0.0009)	-1.36*** (0.001)	-1.36*** (0.001)
<i>Fixed-effects</i>						
Origin (CT)	✓		✓		✓	
Destination (CT)	✓		✓		✓	
Origin (CT)×YEARMONTH		✓		✓		✓
Destination (CT)×YEARMONTH		✓		✓		✓
<i>Fit statistics</i>						
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*

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

Model Setup

- Demand

$$G(\mathbf{p}_n) = \left(\sum_{s=0}^S \alpha_s \left(\left(\sum_{i=1}^N \tilde{p}_{nis}^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}} \right)^{1-\eta} \right)^{\frac{1}{1-\eta}}$$

- Wage Aggregator ($\epsilon < 0$)

$$J(\mathbf{w}_n) = \left(\sum_i (w_{ni})^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}}$$

- Production with Specific Factors

$$Q_{is} = F_{is}(\ell_{is}, m_{is}) = z_{is} \ell_{is}^{\beta_s} m_{is}^{1-\beta_s}$$

Equilibrium

[label=dekequilibrium]

- Market Clearing Condition

$$y_{is} = \sum_{n=1}^N s_{nis} v_n + \sum_{g=1}^G s_{gis} E_g^T$$

- Labor Market Clearing

$$w_{il_i} = \sum_{s=0}^S \theta_s^l \sum_{n=1}^N s_{nis} v_n + \sum_{s=0}^S \theta_s^l \sum_{g=1}^G s_{gis} E_g^T$$

- Disposable Income

$$v_n = \left(\sum_i (w_{ni})^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}} \times T_n$$

Hat Algebra

- Market Clearing Condition

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

- Labor Market Clearing

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

- Disposable Income

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

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

Data Requirements

Data	Description	Comment
I_{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	

Roy's Identity for Labor Supply

- Income maximization problem:

$$v_n = \max_{\{\ell_j\}} \sum_{i=1}^N w_i \ell_i \quad \text{s.t.} \quad H_n(\ell_n) = T_n$$

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

$$\frac{\partial y(\cdot)}{\partial w_j} = \ell_j$$

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

- Differentiating we obtain,

$$\frac{\partial y(\cdot)}{\partial w_j} = - \frac{\frac{\partial h(\mathbf{w}_n, y(\mathbf{w}_n, T_n))}{\partial w_j}}{\frac{\partial h(\mathbf{w}_n, y(\mathbf{w}_n, T_n))}{\partial y}} = \ell_j$$

Derivation of Welfare Formula

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

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

- Totally differentiating,

$$\frac{du_n}{u_n} = \sum_{i=1}^N \frac{1}{J(\mathbf{w}_n)} \frac{\partial (J(\mathbf{w}_n))}{\partial w_i} w_i \frac{dw_i}{w_i} + \sum_{i=1}^N G(\mathbf{p}_n) \frac{\partial (1/G(\mathbf{p}_n))}{\partial p_{ni}} p_{ni} \frac{dp_{ni}}{p_{ni}}$$

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

$$\frac{du_n}{u_n} = \sum_{i=1}^N \frac{\ell_i}{v_n} w_i \frac{dw_i}{w_i} - \sum_{i=1}^N \frac{q_{ni}}{v_n} p_{ni} \frac{dp_{ni}}{p_{ni}}$$

Price Regressions: Group Estimates

Dependent Variables:	δ_{ist}^R	$\delta_{ist}^{T.Dom}$	$\delta_{ist}^{T.For}$	δ_{ist}^R	$\delta_{ist}^{T.Dom}$	$\delta_{ist}^{T.For}$
	OLS			IV - Ref: 2017 Average		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
<i>Variables</i>						
$\ln E_{it}^T$	0.091*** (0.003)	0.485*** (0.005)	0.454*** (0.004)	-0.576*** (0.034)	-0.277*** (0.077)	0.029 (0.056)
<i>Fixed-effects</i>						
Month-Year \times Sector (480)	✓	✓	✓	✓	✓	✓
Location \times Sector (21,920)	✓	✓	✓	✓	✓	✓
Location \times Sector \times Year (43,840)	✓	✓	✓	✓	✓	✓
Location \times Sector \times Month (263,040)	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>						
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

CES Model Example of Simple Non-Parametric Model

- Preferences

$$u_n(\{q_{ni}\}_{i=1,\dots,N}) = \left(\sum_{i=1}^N \alpha_{ni}^{1/\sigma} q_{ni}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}$$

- Constraint

$$\sum_{i=1}^N p_{ni} q_{ni} \leq v_n$$

- Utility max. gives lagrangian

$$\mathcal{L}(\{q_{ni}\}_{i=1,\dots,N}, \lambda) = \left(\sum_{i=1}^N \alpha_{ni}^{1/\sigma} q_{ni}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)} + \lambda \left(v_n - \sum_{i=1}^N p_{ni} q_{ni} \right)$$

CES Model Example of Simple Non-Parametric Model

- FOCs

$$\frac{\partial \mathcal{L}}{\partial q_{ni}} = 0 \iff \left(\sum_{i=1}^N \alpha_{ni}^{1/\sigma} q_{ni}^{(\sigma-1)/\sigma} \right)^{1/(\sigma-1)} \alpha_{ni}^{1/\sigma} q_{ni}^{-1/\sigma} = \lambda p_{ni} \quad \forall i = 1, \dots, N$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = 0 \iff \sum_{i=1}^N p_{ni} q_{ni} = v_n$$

- For two consumption locations i and j

$$\begin{aligned} \left(\frac{\alpha_{ni}}{\alpha_{nj}} \right)^{1/\sigma} \left(\frac{q_{ni}}{q_{nj}} \right)^{-1/\sigma} &= \frac{p_{ni}}{p_{nj}} \\ \frac{\alpha_{ni}}{\alpha_{nj}} &= \frac{p_{ni}^\sigma q_{ni}}{p_{nj}^\sigma q_{nj}} \end{aligned}$$

CES Model Example of Simple Non-Parametric Model

- For two consumption locations i and j

$$\frac{\alpha_{ni}}{\alpha_{nj}} = \frac{p_{ni}^\sigma q_{ni}}{p_{nj}^\sigma q_{nj}}$$
$$q_{nj} = \frac{\alpha_{nj} p_{ni}^\sigma}{\alpha_{ni} p_{nj}^\sigma} q_{ni}$$

- $\times p_{nj}$

$$q_{nj} p_{nj} = \frac{\alpha_{nj} p_{ni}^\sigma}{\alpha_{ni} p_{nj}^\sigma} q_{ni} p_{nj}$$
$$q_{nj} p_{nj} = \frac{1}{\alpha_{ni}} q_{ni} p_{ni}^\sigma \alpha_{nj} p_{nj}^{1-\sigma}$$

CES Model Example of Simple Non-Parametric Model

- \sum_j

$$\sum_j q_{nj} p_{nj} = \frac{1}{\alpha_{ni}} q_{ni} p_{ni}^\sigma \sum_j \alpha_{nj} p_{nj}^{1-\sigma}$$

- using FOC2 (BC)

$$v_n = \frac{1}{\alpha_{ni}} q_{ni} p_{ni}^\sigma P_n^{1-\sigma}$$

- and demand for good i

$$q_{ni} = \alpha_{ni} p_{ni}^{-\sigma} v_n P_n^{\sigma-1}$$

CES Model Example of Simple Non-Parametric Model

- We get indirect utility

$$U_n = \left(\sum_{i=1}^N \alpha_{ni}^{1/\sigma} [\alpha_{ni} p_{ni}^{-\sigma} v_n P_n^{\sigma-1}]^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}$$

$$U_n = P_n^{\sigma-1} v_n \left(\sum_{i=1}^N \alpha_{ni} p_{ni}^{1-\sigma} \right)^{\sigma/(\sigma-1)} = P_n^{\sigma-1} v_n P_n^{-\sigma}$$

$$U_n = \frac{v_n}{P_n} = \frac{v_n}{\left(\sum_{i=1}^N \alpha_{ni} p_{ni}^{1-\sigma} \right)^{1/(1-\sigma)}}$$

- We can also express demand as total spending

$$X_{ni} = p_{ni} q_{ni} = \alpha_{ni} \left(\frac{p_{ni}}{P_n} \right)^{1-\sigma} v_n$$

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 - consumption of goods $i = 1, \dots, N$ to maximize utility s.t. income $\sum_i p_{ni} q_{ni} \leq v_n \rightarrow q_{ni}(\mathbf{p}_n; v_n)$
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- Residents Blocks are separated by *(iceberg) commuting and trade costs*.
 - so that: $p_{nj} = \tau_{nj} p_j$ and $w_{ni} = \mu_{ni} w_i$.

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- Tourists have the same preferences over consumption in blocks $i = 1, \dots, N$
- Markets clear
 - Goods market clearing in location i : $y_i = E_i^R + E_i^T = \sum_{n=1}^N s_{ni} v_n + s_i^T E^T$
 - Labor market clearing in location i : $\frac{w_i \ell_i}{\theta_i^\ell} = y_i = \sum_{n=1}^N s_{ni} v_n + s_i^T E^T$

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