Urban Welfare: Tourism in Barcelona

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** The views expressed herein are those of the authors and not necessarily those of CaixaBank, the Federal Reserve Bank of Atlanta, or the Federal Reserve System.*

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  - Unclear identification

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- Apply methodology to estimate welfare effect of tourism in Barcelona:
  - Rich new data on expenditure and income spatial patterns
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  - 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-Iino (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 $\{1, ..., N\} \equiv \mathcal{N}$ **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 $E^T \equiv \{E_1^T, ..., E_N^T\}$ on residents $\{1, ..., N\}$ 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:

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

$$\underbrace{H_n \left(\{l_{ni}\}_{i \in \mathcal{N}} \right)}_{\text{increasing \& weakly convex}} \leq \underbrace{T_n}_{\text{fixed labor endowment}}$$

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- Homothetic demand $\implies u_n = v_n/G\left(\mathbf{p}_n\right)$, 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 $\boldsymbol{u}_n = \frac{T_n \overbrace{J(\boldsymbol{w}_n)}^{\text{Wage aggregator}}}{\underbrace{G(\boldsymbol{p}_n)}_{\text{Price aggregator}}}$

- Then envelope theorem yields

$$\mathbf{d}\ln \mathbf{u}tility_n = \underbrace{\sum_i \mathbf{c}ommuting_{n\to i} \times \partial \ln \mathbf{w}ages_i}_{\Delta\text{Spatial Income}} - \underbrace{\sum_i \mathbf{s}pending_{n\to i} \times \partial \ln \mathbf{p}rices_i}_{\Delta\text{Spatial Price Index}} \tag{1}$$

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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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  - Firm income is equal to total sales:

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

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

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

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

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

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

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

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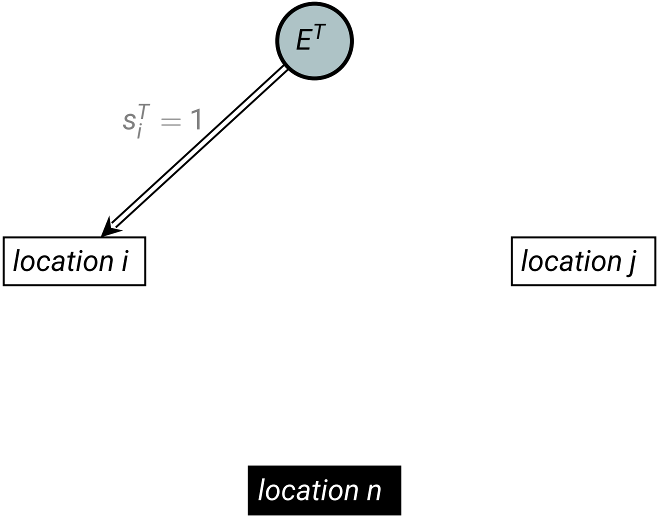
! *Short-run* GE response to *local* shocks in *static* framework.

Intuition for the GE propagation

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



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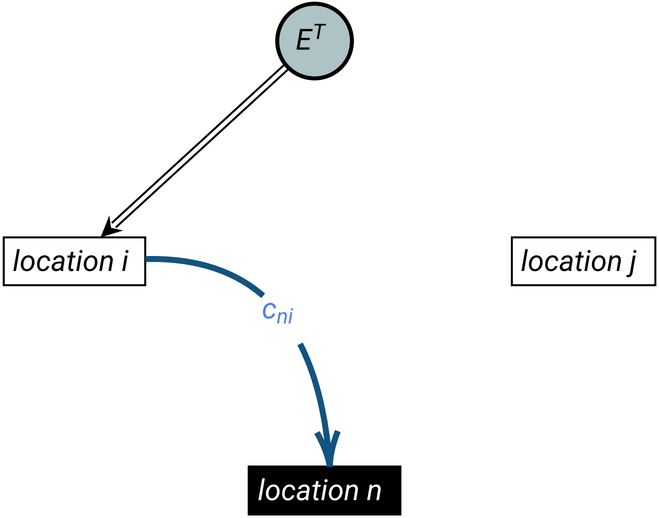
Consider external **demand shock** E^T to a city $\rightarrow$ **Income Shock**



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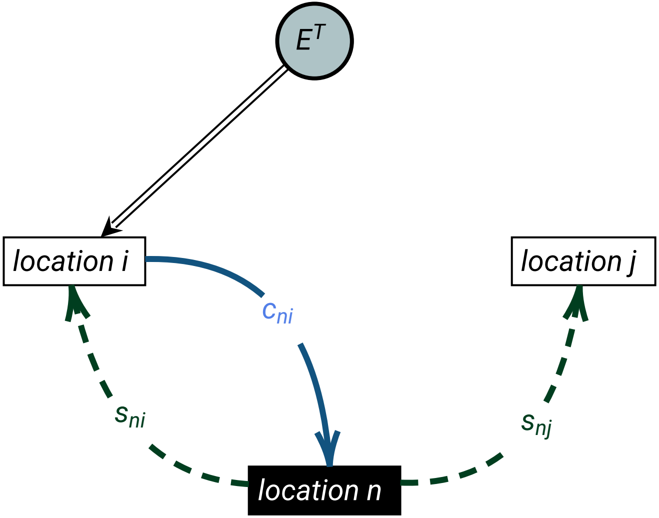
Consider external **demand shock** E^T to a city $\rightarrow$ **Income Shock** $\rightarrow$ **Demand**



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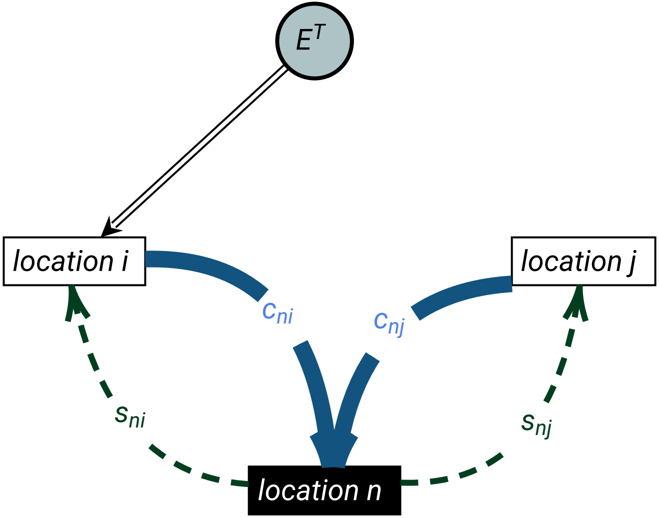

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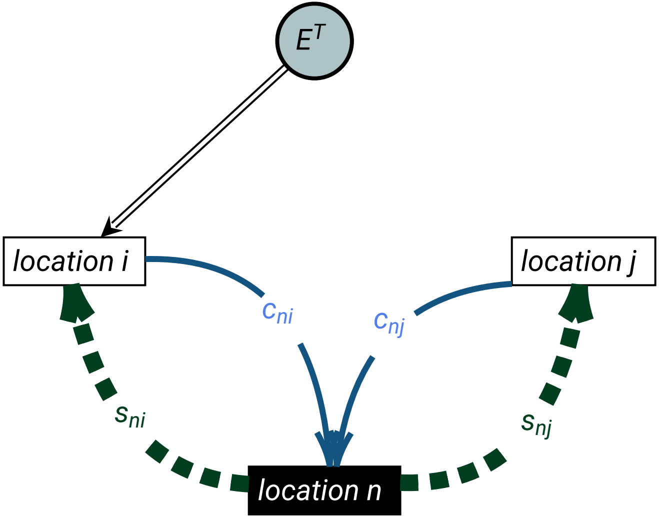

Insight 2: Analytical expressions for GE propagation of shocks, ctd.

- Solving the system and using a Neumann series expansion:

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

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- And similarly for residential incomes:

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

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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: $\{\partial \ln p_i, \partial \ln v_n\}_{i=1}^{N}$ to an exogenous shock $\partial \ln E^T$ (next)

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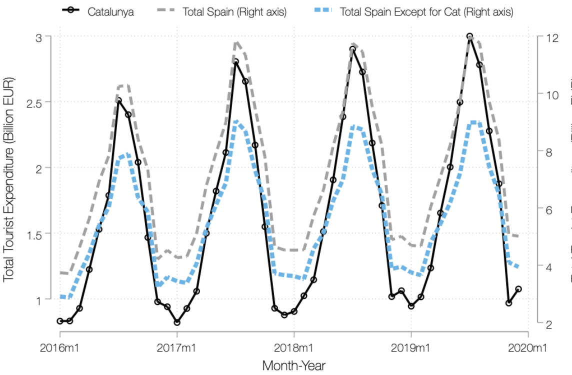

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New Generation of High Resolution Urban Datasets

- 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) $\sim$ 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
  - + Alternative commuting patterns from cell phone locations (INE)

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

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
  + Alternative commuting patterns from cell phone locations (INE)

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

$\rightarrow$ Identification strategy for elasticities

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

$\rightarrow$ Consumption and Income shares

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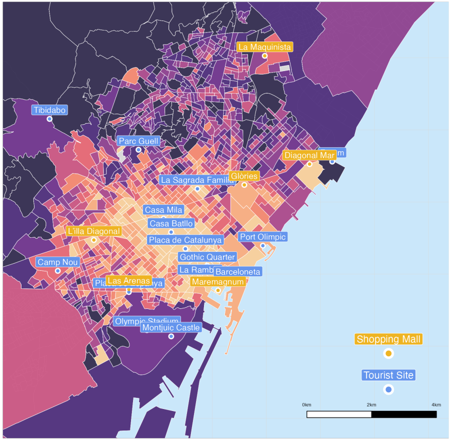
Fact 1A: Tourist spending varies across space

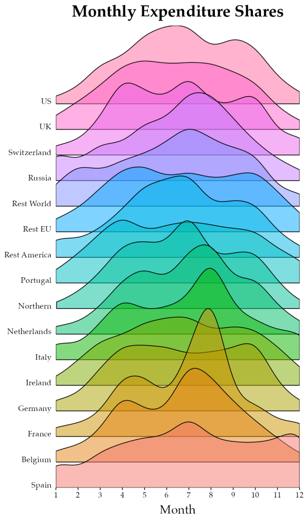


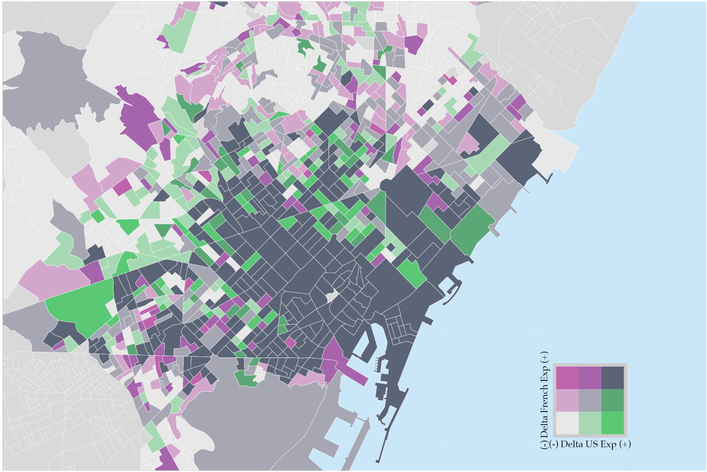
Average (yearly) expenditure per sqm by tourists.

0 – 0.4EUR
0.4 – 0.88EUR
0.88 – 1.36EUR
1.36 – 2.11EUR
2.11 – 3.19EUR
3.19 – 4.8EUR
4.8 – 7.87EUR
7.87 – 14.52EUR
14.52 – 31.77EUR
31.77 – 1658.87EUR

Tourist Spending Time Series

FACT 1B: Tourism varies across time within the city





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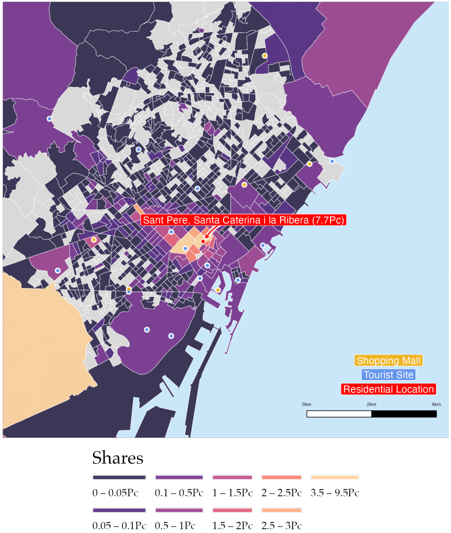
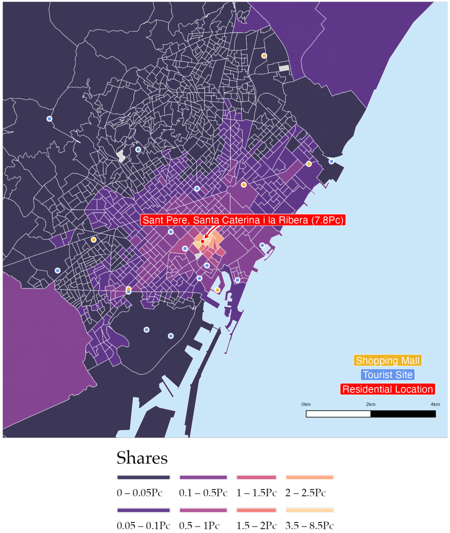
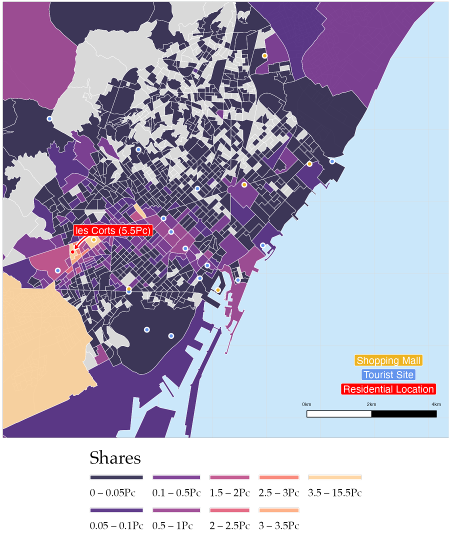


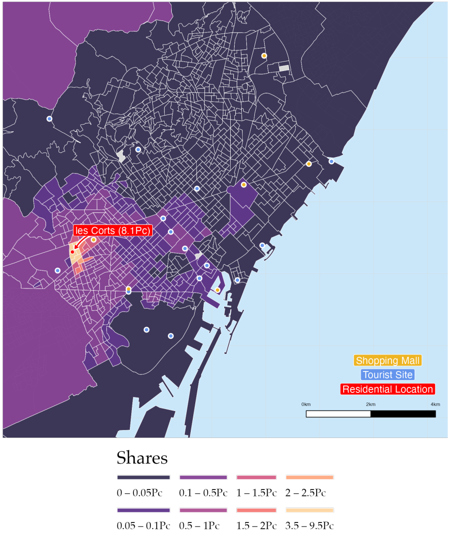


Cross-Sec. Local Spending Cross-Sec. Income

Exp Gravity Commuting Gravity

Fact 2: Locals spending and income patterns vary by residence





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

Outline of Talk

A General Methodology for (small) Urban Shocks

Tourism in Barcelona

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

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

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

From Theory to **Estimation**

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

- 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:

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

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

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

First Stage

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:

$$\ln p_{it} = \beta_1 \ln E^T_{jt} + \underbrace{\beta_2 \left(1 + [M_{ii}] + \ldots\right) \left(\frac{E^T_{i0}}{y_{i0}}\right) \ln E^T_{it}}_{\text{GE HTE of own shock}}$$

$$+ \underbrace{\beta_3 \sum_{j \neq i} \left([M_{ij}] + \ldots\right) \left(\frac{E^T_{j0}}{y_{j0}}\right) \ln E^T_{jt}}_{\text{GE spillovers from shocks elsewhere}} + \delta_i + \delta_t + \varepsilon_{it}$$

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 R^2	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*	-0.0357
	(0.0292)	(0.0258)
Tourist Spending Everywhere (GE)		0.3449***
		(0.0607)
GE *Locally*		
Spillovers from *Elsewhere*		
Fixed-effects		
Census Tract	Yes	Yes
Year-Month	Yes	Yes
N	25,379	25,379
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	ATE: No Spatial Spillovers	**GE (exact sum): All Spatial Spillovers**	**GE (exact sum): Own/Else Spillovers**
Local Tourist Spending	0.0536*	-0.0357	-0.0357
	(0.0292)	(0.0258)	(0.0263)
Tourist Spending Everywhere (GE)		0.3449***	
		(0.0607)	
GE *Locally*			0.3306***
			(0.0558)
Spillovers from *Elsewhere*			0.4184***
			(0.1463)
Fixed-effects			
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
- GE Exact $\equiv$ Leontief Inverse

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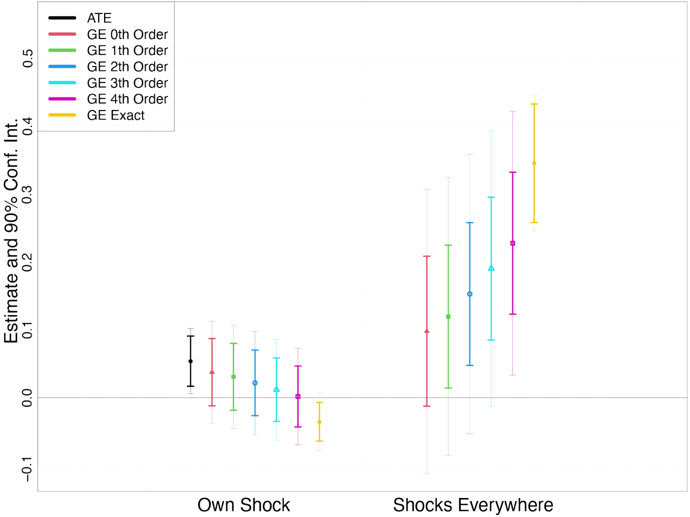

- Thinner C.I: Driskoll-Kraay S.E.
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Effect of tourism on incomes

DEPENDENT VARIABLE: LOG LOCAL EARNINGS

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

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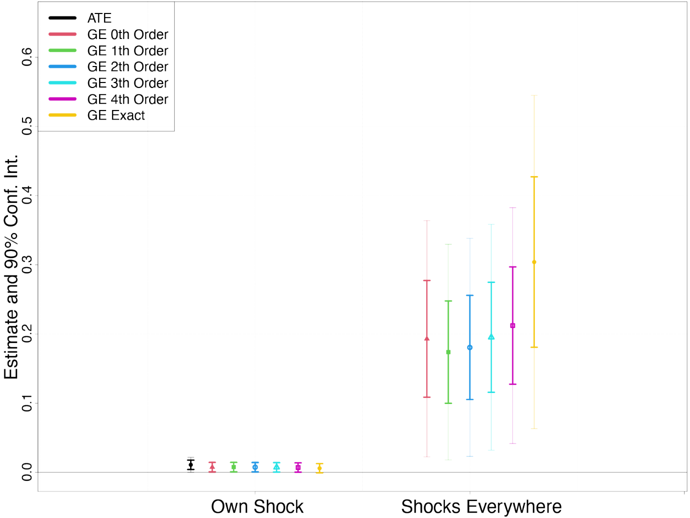

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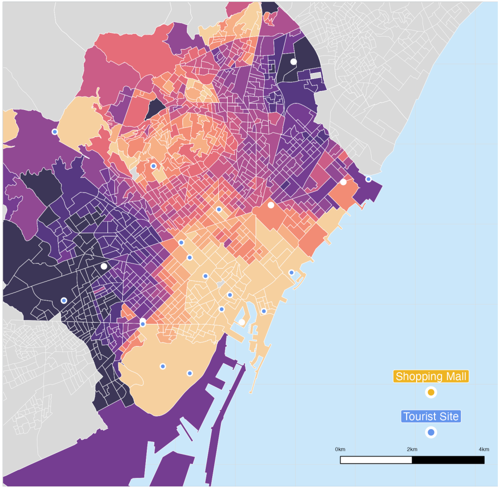
Is tourism *good* for locals?

- 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)

8.9 – 10.31 Pc
10.5 – 10.61 Pc
10.71 – 10.78 Pc
10.83 – 10.9 Pc
10.99 – 11.15 Pc
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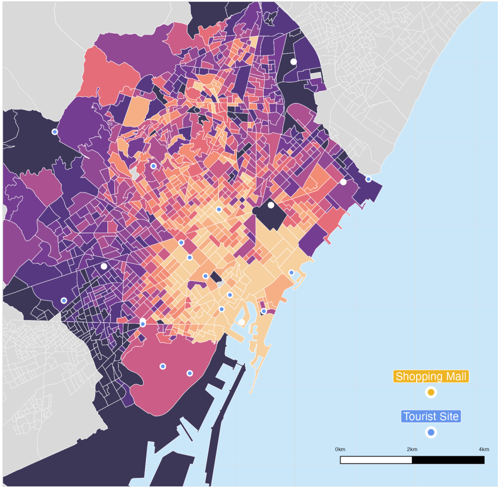
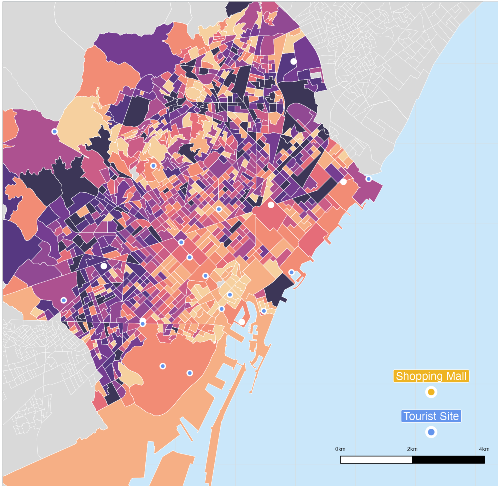
10.61 – 10.71 Pc
10.78 – 10.83 Pc
10.9 – 10.99 Pc
11.15 – 12.73 Pc



Change in Price Index (GE)

4.81 – 8.17 Pc
8.57 – 8.75 Pc
8.91 – 9.03 Pc
9.15 – 9.27 Pc
9.41 – 9.63 Pc
8.17 – 8.57 Pc
8.75 – 8.91 Pc
9.03 – 9.15 Pc
9.27 – 9.41 Pc
9.63 – 11.75 Pc

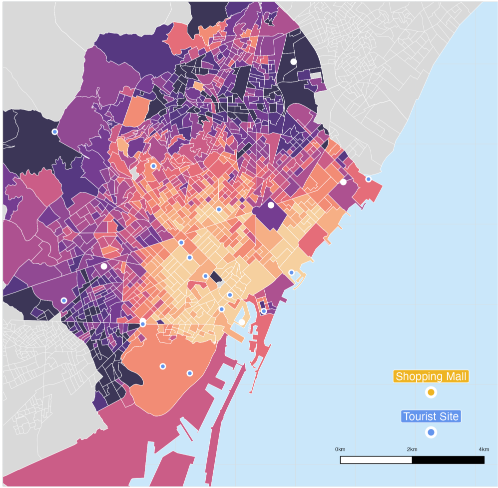
Income (Panel A) and Price Effects (Panel B) - ATE



Change in Income (ATE)

-0.95 – 0.36 Pc | 0.41 – 0.44 Pc | 0.47 – 0.5 Pc | 0.52 – 0.55 Pc | 0.58 – 0.62 Pc

0.36 – 0.41 Pc | 0.44 – 0.47 Pc | 0.5 – 0.52 Pc | 0.55 – 0.58 Pc | 0.62 – 2.31 Pc

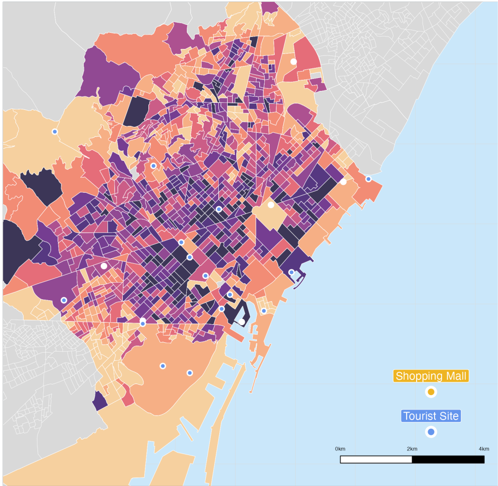


Change in Price Index (ATE)

1.05 – 1.67 Pc | 1.74 – 1.79 Pc | 1.84 – 1.89 Pc | 1.94 – 1.99 Pc | 2.07 – 2.16 Pc

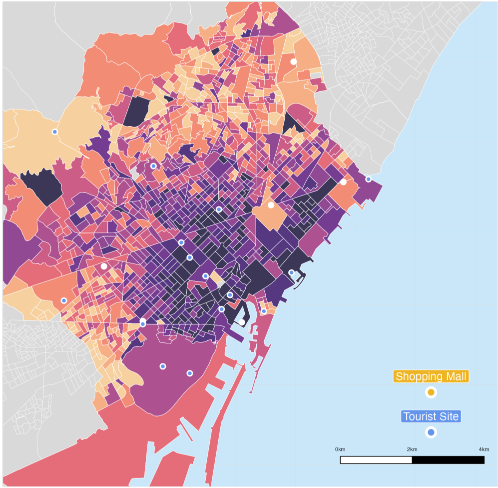
1.67 – 1.74 Pc | 1.79 – 1.84 Pc | 1.89 – 1.94 Pc | 1.99 – 2.07 Pc | 2.16 – 2.48 Pc

Welfare Effects: With and without GE spillovers



Change in Welfare (GE)

0.73 – 1.34 Pc | 1.46 – 1.54 Pc | 1.63 – 1.71 Pc | 1.81 – 1.91 Pc | 2.09 – 2.42 Pc
1.34 – 1.46 Pc | 1.54 – 1.63 Pc | 1.71 – 1.81 Pc | 1.91 – 2.09 Pc | 2.42 – 5.82 Pc



Change in Welfare (ATE)

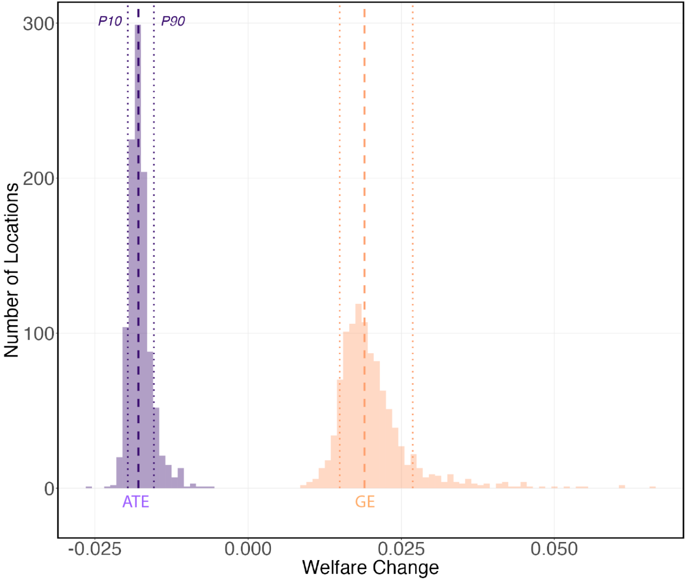
-2.63 – -1.63 Pc | -1.57 – -1.51 Pc | -1.46 – -1.42 Pc | -1.38 – -1.33 Pc | -1.26 – -1.13 Pc
-1.63 – -1.57 Pc | -1.51 – -1.46 Pc | -1.42 – -1.38 Pc | -1.33 – -1.26 Pc | -1.13 – 0.37 Pc

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?

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  - Frechet distribution of firm & resident productivities
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- With structural elasticities calibrated to match:
  - Income responses to tourism (commuting elasticity 4.65)
  - Expenditure responses to prices (demand elasticity $\sim$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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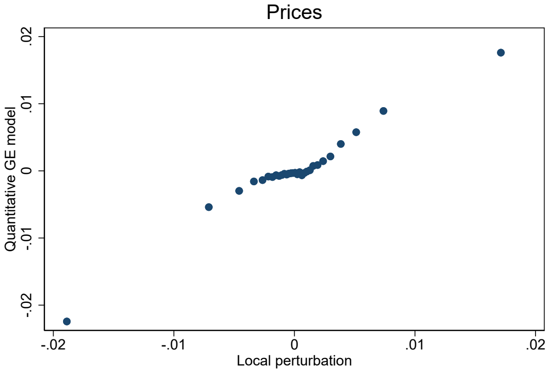
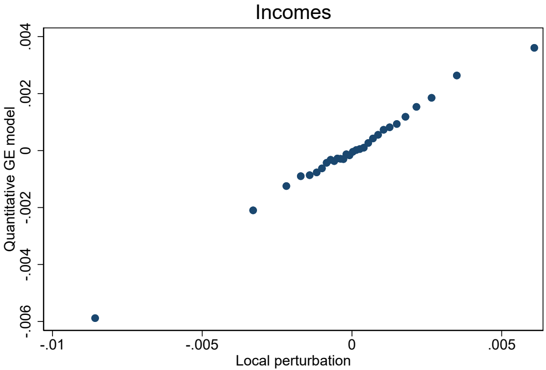
- Delivers the same GE market clearing conditions as above.
- But can now solve for exact (non short-run, non-local) changes in prices and incomes.
- *Question*: Does this quantitative GE model better explain the data?

Comparison to full quantitative model: Predictions are very similar



Location and month-year fixed effects.



Location and month-year fixed effects.

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***		1.104**
	(0.267)		(0.418)
Quantitative GE model		0.149	-0.117
		(0.379)	(0.405)
Fixed-effects			
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**		0.685
	(0.450)		(0.424)
Quantitative GE model		1.000*	0.656
		(0.501)	(0.498)
Fixed-effects			
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.*

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

Conclusion

- New method to estimate the welfare impact of spatial shocks
  - Avoids parametric assumptions, "let’s the data speak"
  - Incorporates GE spatial linkages

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  - Avoids parametric assumptions, "let’s the data speak"
  - Incorporates GE spatial linkages
- Estimate the welfare effect of tourism on locals
  - Unique urban spending and income spatial networks data
  - Identification based on timing/preferences of different tourist groups

Conclusion

- New method to estimate the welfare impact of spatial shocks
  - Avoids parametric assumptions, "let's the data speak"
  - Incorporates GE spatial linkages
- Estimate the welfare effect of tourism on locals
  - Unique urban spending and income spatial networks data
  - 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

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

- 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,

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

back

Shift-Share Instrument: Derivations

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

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

- 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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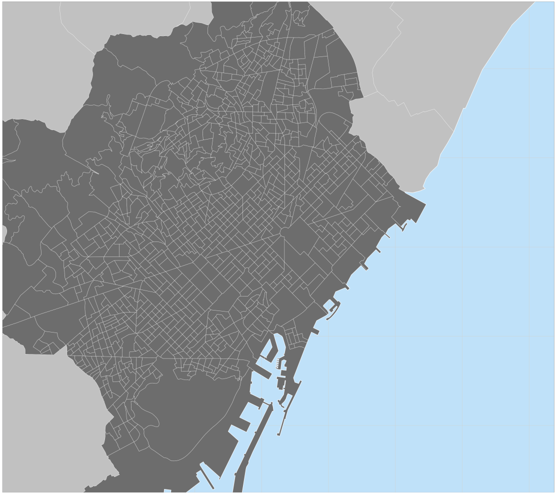
Data Appendix

Sample of Locations

Coverage Area: Inner (dark) and Outer (light) Barcelona



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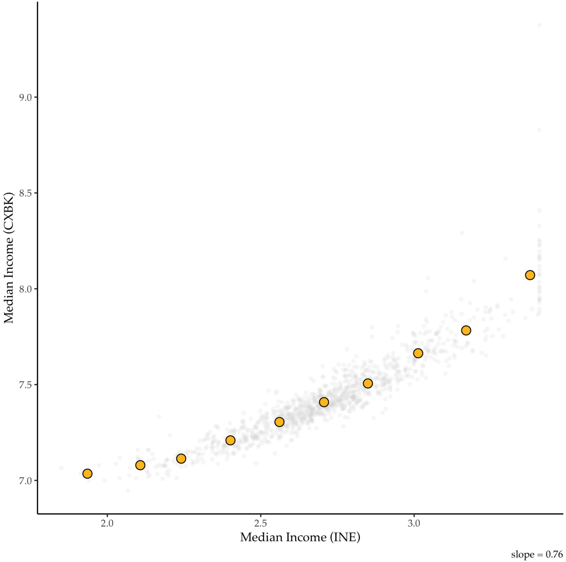
Income Data: Comparison with Administrative Data



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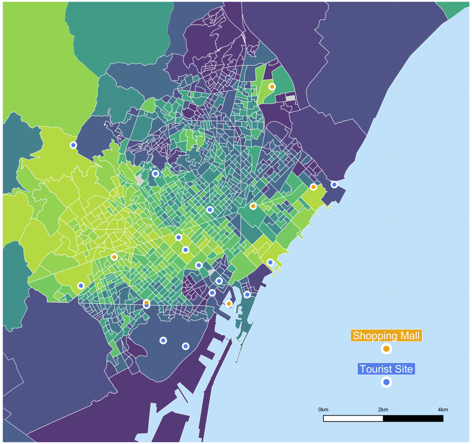
Income Distribution across Barcelona



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

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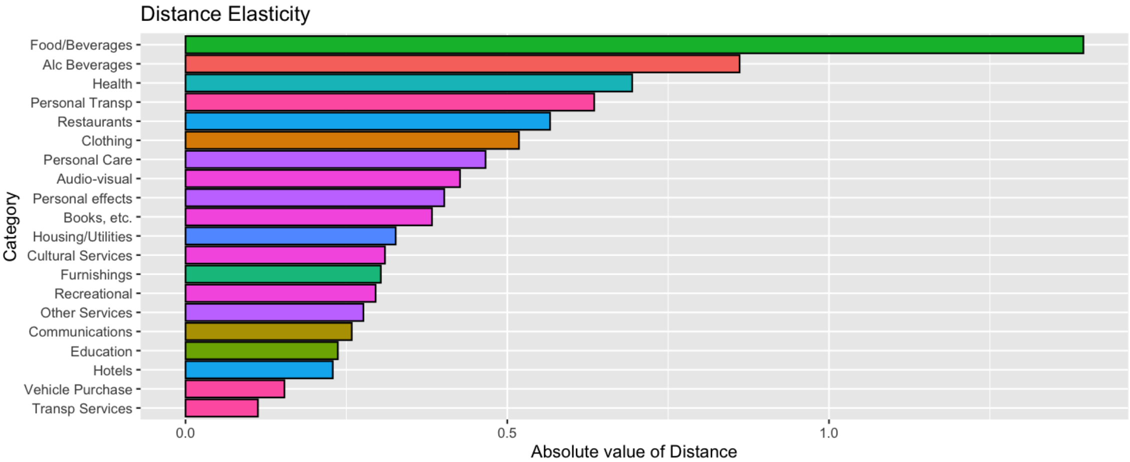
Empirical Analysis Appendix

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*** (0.107)	-1.51*** (0.037)	-1.17*** (0.054)	-1.53*** (0.028)	-0.134*** (0.002)	-0.411*** (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*

back

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)**
Fixed Effects		
Census Tract	Yes	Yes
N	1,728	1,718
Within R^2	0.004	0.001

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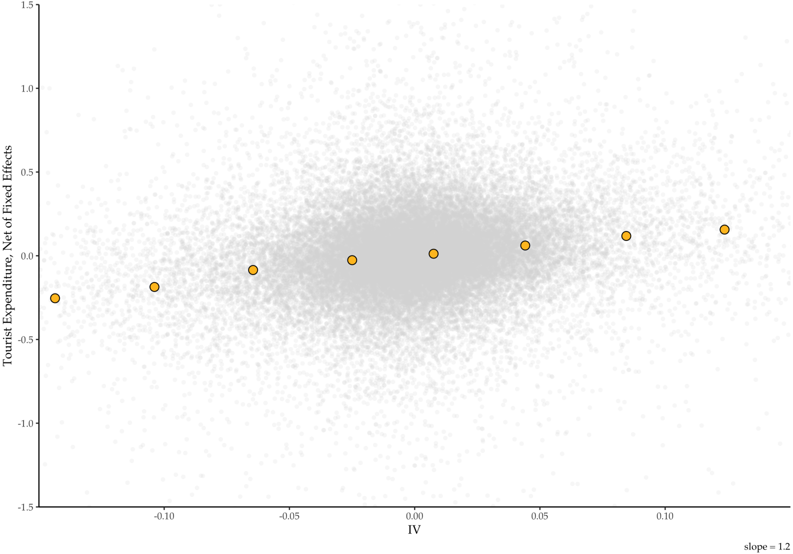
Shift Share: First Stage



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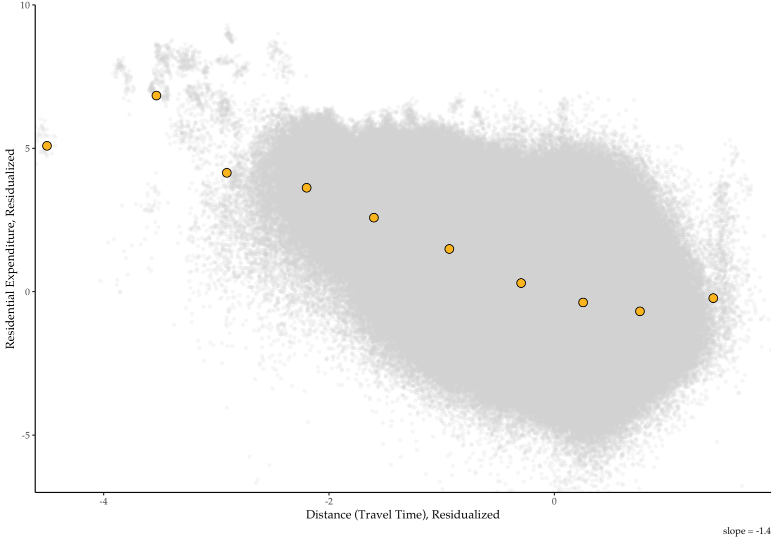
Fit of Gravity Specification



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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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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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Model Setup

- Demand

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

- Wage Aggregator ($\epsilon < 0$)

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

- Production with Specific Factors

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

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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

$$w_i \ell_i = \sum_{s=0}^{S} \theta_s^\ell \sum_{n=1}^{N} s_{nis} v_n + \sum_{s=0}^{S} \theta_s^\ell \sum_{g=1}^{G} s_{gis} E_g^T$$

- Disposable Income

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

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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

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

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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 $y(\boldsymbol{w}_n, T_n)$ and envelope theorem implies,

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

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

- Differentiating we obtain,

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

back

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,

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

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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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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

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

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

- For two consumption locations i and j

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

CES Model Example of Simple Non-Parametric Model

- For two consumption locations ***i*** and ***j***

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

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

- $\times p_{nj}$

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

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

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

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

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

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

- We can also express demand as total spending

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

Theory: Simple Spatial Model

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- Residents of block $n = 1, ..., N$ have homothetic preferences and choose
  - consumption of goods $i = 1, ..., N$ to maximize utility s.t. income $\sum_i p_{ni} q_{ni} \leq v_n \rightarrow q_{ni}(\boldsymbol{p}_n; v_n)$
  - supply of labor to $i = 1, ..., N$ to max income $\sum_i w_i \ell_i$ s.t. time constraint $T_n \rightarrow l_{ni}(\boldsymbol{w}_n; T_n)$

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- Residents Blocks are separated by *(iceberg) commuting and trade costs*.
  - so that: $p_{nj} = \tau_{ni} p_j$ and $w_{ni} = \mu_{ni} w_i$.

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- Residents Blocks are separated by *(iceberg) commuting and trade costs.*
  - so that: $p_{nj} = \tau_{ni} p_j$ and $w_{ni} = \mu_{ni} w_i$.
- Tourists have the same preferences over consumption in blocks $i = 1, ..., N$

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  - Combining labor and a specific factor with labor share θ_i^ℓ
- Residents of block $n = 1, ..., N$ have homothetic preferences and choose
  - consumption of goods $i = 1, ..., N$ to maximize utility s.t. income $\sum_i p_{ni} q_{ni} \leq v_n \rightarrow q_{ni}(\boldsymbol{p}_n; v_n)$
  - supply of labor to $i = 1, ..., N$ to max income $\sum_i w_i \ell_i$ s.t. time constraint $T_n \rightarrow l_{ni}(\boldsymbol{w}_n; T_n)$
- Residents Blocks are separated by *(iceberg) commuting and trade costs.*
  - so that: $p_{nj} = \tau_{ni} p_j$ and $w_{ni} = \mu_{ni} w_i$.
- Tourists have the same preferences over consumption in blocks $i = 1, ..., N$
- 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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