# Urban Welfare: Tourism in Barcelona


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LSE
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# New Wave of Urban Research

A. New generation of urban spatial equilibrium models (Ahlfeldt *et al.* , 2015; Allen & Arkolakis, 2016)
  - Structural counterfactuals at a high resolution
  - ... but restrictive parametric assumptions and/or structural estimation

B. New generation of **urban data**
  - Urban economic activity can be observed in unprecedented detail
  - Mobility, expenditure, income networks (cellphone, banks, apps)
  - ... but hard to implement tractable and informative empirical analysis

- Welfare effects of an urban shock...

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- Welfare effects of an urban shock...

  ... in a tractable way without parametric assumptions or structural estimation?

# This Paper: A method to estimate welfare effects of urban shocks

1. Both simple and general:
   - Simple: Regression based framework
   - General: No parametric assumptions necessary
2. Based on two insights:
   - Envelope results from residents' optimal (spatial) cons & commuting patterns

     $\Rightarrow$ Intuitive analytical expression for intra-city welfare
   - Perturbation of market clearing identifies **heterogeneous effects** & **GE spillovers**

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   - Envelope results from residents' optimal (spatial) cons & commuting patterns
     $\Rightarrow$ Intuitive analytical expression for intra-city welfare
   - Perturbation of market clearing identifies **heterogeneous effects** & **GE spillovers**
3. Apply methodology to estimate welfare effect of tourism in Barcelona:
   - Rich new data on expenditure and income spatial patterns
   - Causal (shift-share) identification from variation in vacation timing in RoW

# Tourism as an Urban Shock

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  - 7% of world exports
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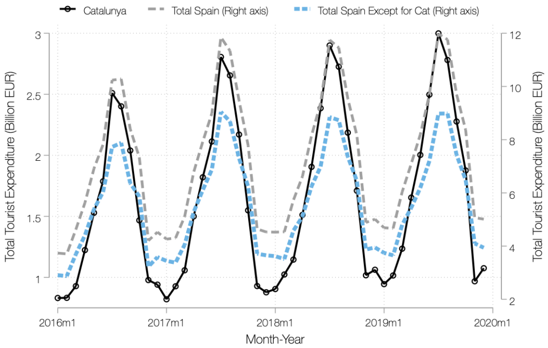
- Growing, especially in cities
  - BCN: 25% secular ↑ in past 5 yrs
  - BCN: 200% seasonal ↑ within year



# Tourism as an Urban Shock

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- Growing, especially in cities
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- Unequal welfare gains

# Key Findings

1. Methodological
   - Simple reduced form approach has problems (Aggr. bias + SUTVA violation)
   - Incorporating theory-predicted heterogeneity and spillovers identifies het effects
   - Predictions close to those from 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

# 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)

# Outline of Talk

**A General Methodology for (small) Urban Shocks**

Intra-city Patterns of Consumption & Income

Empirical Strategy and Identification

Welfare Effects Across the City

Comparison with a Quantitative Model

Conclusion

# An Envelope Result for the Welfare effects of Small Shocks

- Arbitrary discrete urban geography: $N$ blocks, each with resident(s) and firm(s).

- Resident of block $n = 1, ..., N$ chooses goods $i = 1, ..., N$ to (spatially) consume.

$$u_n = \frac{v_n}{G(\boldsymbol{p}_n)}$$

  - homothetic preferences
  - $v_n$ is disposable income of representative agent in block $n$
  - $G(\cdot)$ is a price aggregator
  - $\boldsymbol{p}_n$ refers to the set of transport-cost and amenity adjusted prices

# An Envelope Result for the Welfare effects of Small Shocks

- Supplies labor (spatially) to maximize income.

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

  - $T_n$ is the time endowment in location $n$ scaled by population size
  - $H_n(\cdot)$ is a convex function that reflects congestion costs in commuting
  - $\boldsymbol{\ell}_n$ is the vector of commuting cost adjusted labor supply

Roys Identity for Labor Supply

# Intuitive analytical expression for intra-city welfare analysis

**Theorem (Welfare Effect of a (small) Shock)**

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

$$d\ln u_n = \underbrace{\sum_i c_{ni} \times \partial \ln w_i}_{\Delta \textit{Spatial Income}} - \underbrace{\sum_i s_{ni} \times \partial \ln p_i}_{\Delta \textit{Spatial Price Index}} .$$

- Evaluating the welfare effects of an urban shock requires:
  - Income share data $\{c_{ni}\}_{n=1,i=1}^{N,N}$
  - Spatial expenditure data $\{s_{ni}\}_{n=1,i=1}^{N,N}$
  - Estimates of key elasticities: $\{\partial \ln p_i, \partial \ln w_i\}_{i=1}^{N}$

Deriving Welfare Formula

# Heterogeneous Effects & GE Spillovers

Consider an external **expenditure shock** $E^T$ to a city

- Goods market clearing in location $i$:

$$y_i = \sum_{n=1}^{N} s_{ni} v_n + s_i^T E^T$$

- Labor market clearing in location $i$:

$$\frac{w_i \ell_i}{\theta_i^\ell} = \sum_{n=1}^{N} s_{ni} v_n + s_i^T E^T$$

  - where $\theta_i^\ell$ is the output elasticity to labor

# Heterogeneous Effects & GE Spillovers

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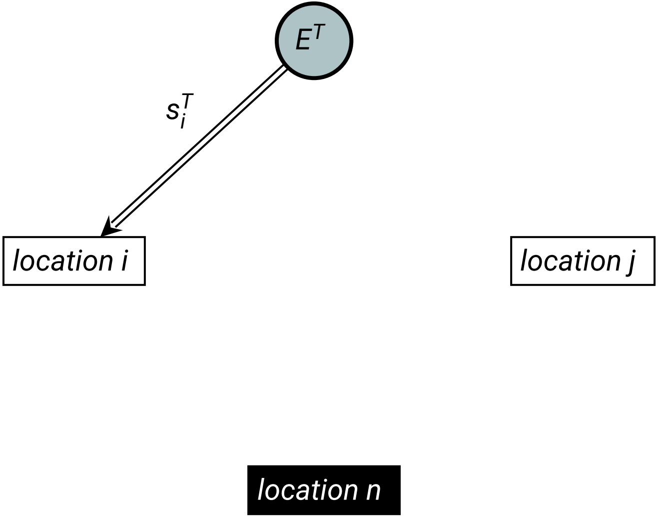
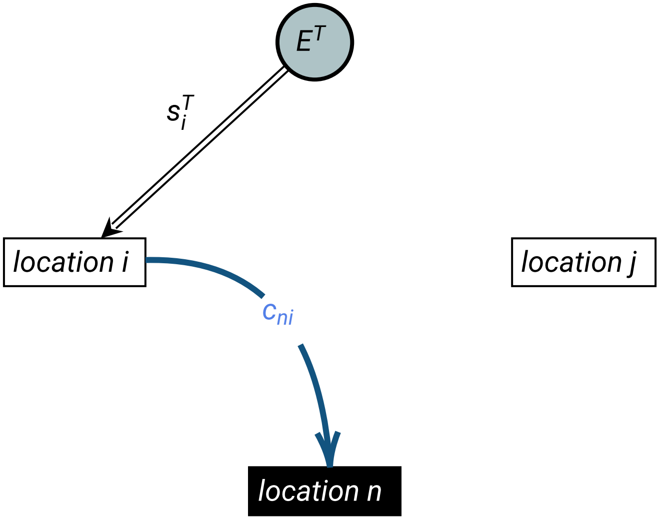


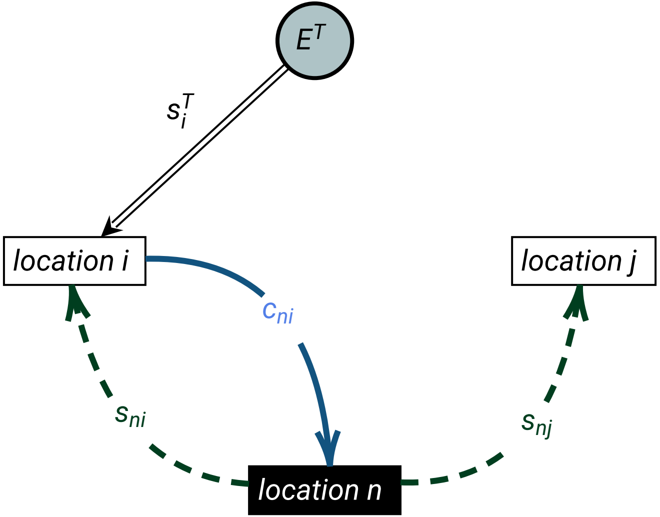
# Heterogeneous Effects & GE Spillovers

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



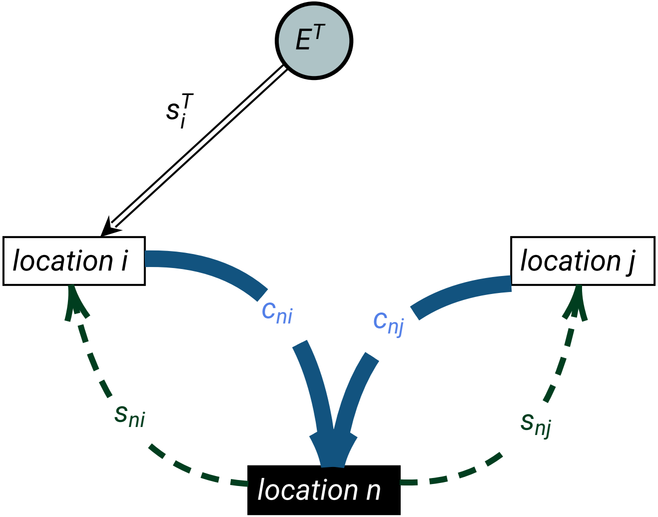
# Heterogeneous Effects & GE Spillovers

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



# Heterogeneous Effects & GE Spillovers

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



# Heterogeneous Effects & GE Spillovers

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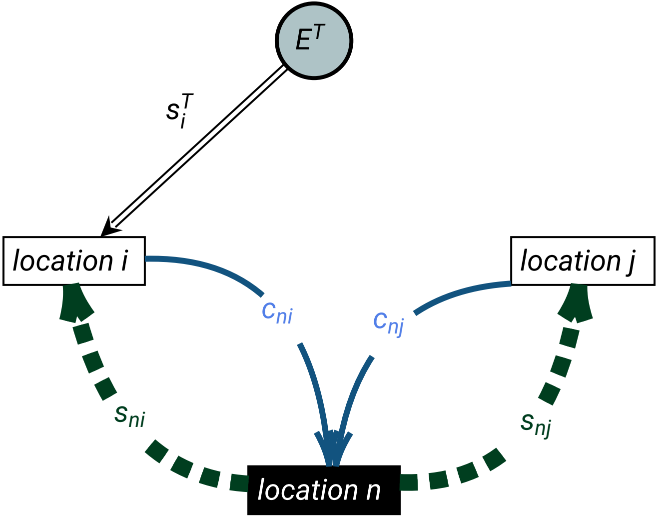

# Heterogeneous Effects & GE Spillovers

- **Direct Effect:**
  - Expenditure shock increases prices/wages $\propto$ to its expenditure share in that location
- **Indirect Effect:**
  - Increases prices/wages by increasing residential income elsewhere (spatial multiplier)

# Heterogeneous Effects & GE Spillovers

## Elasticities: Theory Insights

### Theorem ('Short Run' Elasticities for Prices and Wages)

*Consider an external expenditure shock $E^T$ to a city. Imposing market clearing, keeping expenditure shares and labor allocation constant, we obtain,*

$$\frac{\partial \ln p_i}{\partial \ln E^T} = \underbrace{\frac{E_i^T}{y_i}}_{\text{Direct Effect}\left(\eta_{itm}^{0,T}\right)} \underbrace{+\frac{1}{y_i}\sum_n s_{ni} \times v_n \times \sum_j c_{nj} \times \frac{\partial \ln w_j}{\partial \ln E^T}}_{\text{GE Spillover via Spatial Exp Patterns}}$$

$$\frac{\partial \ln w_i}{\partial \ln E^T} = \underbrace{\frac{E_i^T}{y_i}}_{\text{Direct Effect}\left(\eta_{itm}^{0,T}\right)} \underbrace{+\frac{1}{y_i}\sum_n s_{ni} \times v_n \times \sum_j c_{nj} \times \left(\frac{E_j^T}{y_j}\right) + \ldots.}_{\text{GE Spillover via Spatial Exp Patterns}}$$

# Heterogeneous Effects & GE Spillovers

- A General Methodology for (small) Urban Shocks
  - Intuitive analytical formula to trace out welfare effects
  - Predictions for heterogeneous and GE effects

# Outline of Talk

A General Methodology for (small) Urban Shocks

**Intra-city Patterns of Consumption & Income**

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# New Generation of High Resolution Urban Datasets

- Working closely with Caixabank, a large 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.

# New Generation of High Resolution Urban Datasets

- Expenditure Data:
- Income Data:
- Commuting data:

# New Generation of High Resolution Urban Datasets

- Expenditure Data:
  - Source: Account & point-of-sale data covering 165M+ transactions pa
  - Locals: 1095 residential tiles x 1095 cons tiles x 20 sectors x 36 months
  - Tourists: country of origin x 1095 cons tiles x 20 sectors x 36 months
  - January 2017 - December 2019
  - Covers roughly 54.4 pc of total expenditure Comparison: HBS

- Income Data:

- Commuting data:

# New Generation of High Resolution Urban Datasets

- Expenditure Data:

- Income Data:
  - Source: Payrolls and UB from over 400k accounts
  - Mean and median income per census tract Comparison: INE Map: Income in Barcelona

- Commuting data:

# New Generation of High Resolution Urban Datasets

- Expenditure Data:

- Income Data:

- Commuting data: Two sources:
  1. Imputed from expenditures on weekday lunches (Caixa)
  2. Commuting patterns from cell phone locations (INE)

# New Generation of High Resolution Urban Datasets

- Expenditure Data:
- Income Data:
- Commuting data:
- Housing prices:
  - Source: Idealista ("Spanish Zillow")
  - House prices and rental rates
  - Monthly frequency for neighborhoods (more aggregated than census blocks)

# Three Stylized Facts

1. Tourism varies across space and time within the city
2. Locals' spending and income are spatially determined by residence
3. Tourist spending affects local's spending and incomes

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$$d \ln u_n = \underbrace{\sum_i c_{ni} \times \partial \ln w_i}_{\Delta\text{Spatial Income}} - \underbrace{\sum_i s_{ni} \times \partial \ln p_i}_{\Delta\text{Spatial Price Index}} .$$

1. Tourist spending varies across space and time within the city
   - Provides variation for identification
2. Locals' spending and income are spatially determined by residence
   - Documents the heterogeneous incidence across space
3. Tourist spending affects local's spending and incomes
   - Prima-facie evidence of the effect of tourism

# Three Stylized Facts

1. **Tourism varies across space and time within the city**
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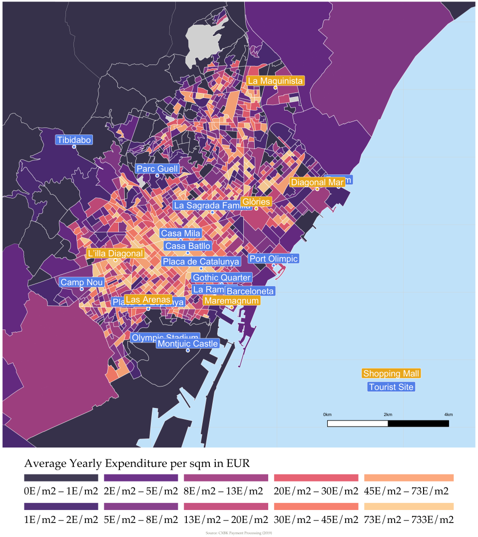
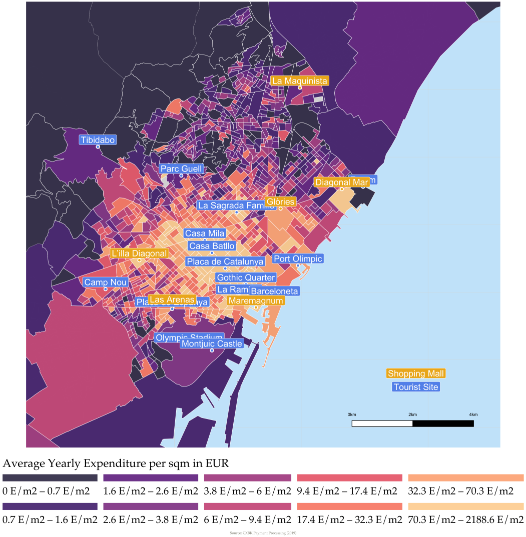
# Fact 1: Tourism varies across space and time within the city

Local Expenditures in Barcelona




Tourist Expenditures in Barcelona



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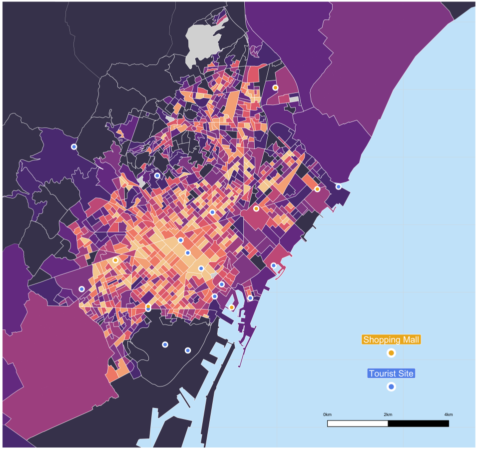


Average Yearly Expenditure per sqm in EUR

0E/m2 – 1E/m2 | 2E/m2 – 5E/m2 | 8E/m2 – 13E/m2 | 20E/m2 – 30E/m2 | 45E/m2 – 73E/m2

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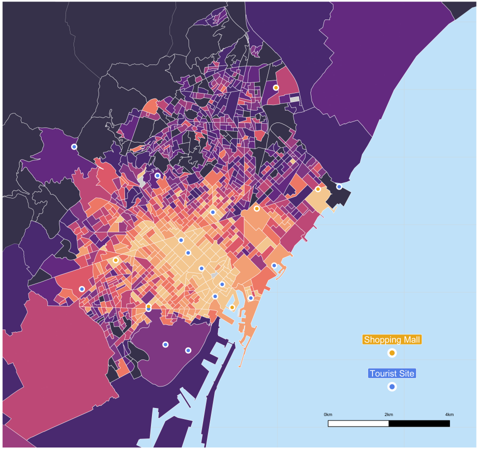
Source: CXBK Payment Processing (2019)

Tourist Expenditures in Barcelona




Average Yearly Expenditure per sqm in EUR

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

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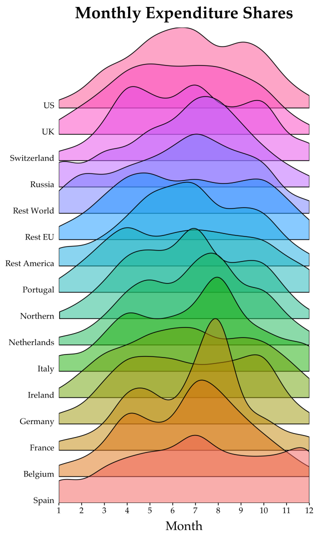


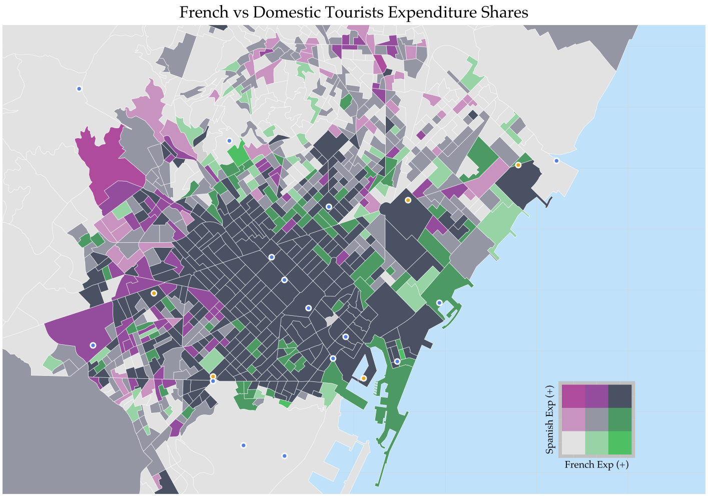

# Three Stylized Facts

1. Tourism varies across space and time within the city
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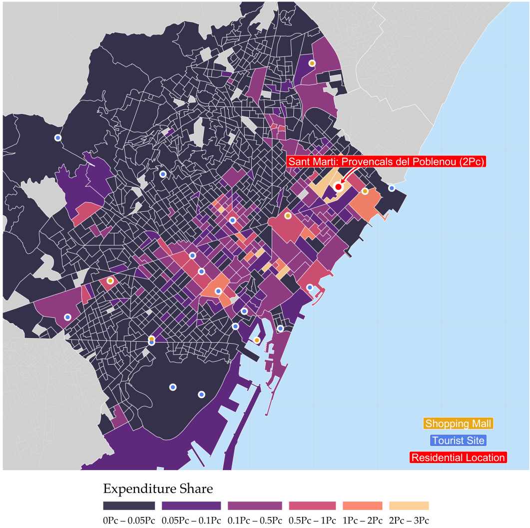
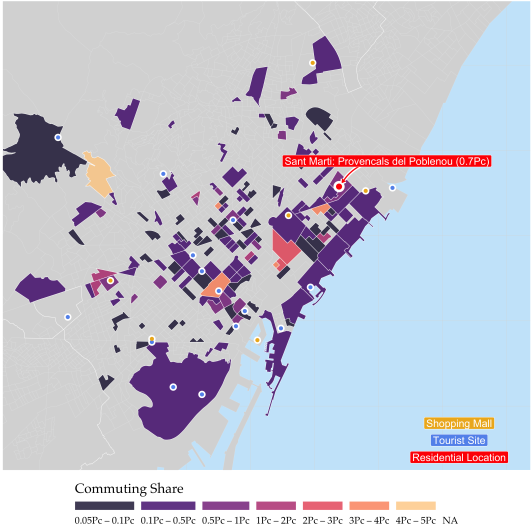
# Fact 2: Local Spending & Income is Spatial

Spatial Expenditure Patterns




Spatial Commuting Patterns



# Three Stylized Facts

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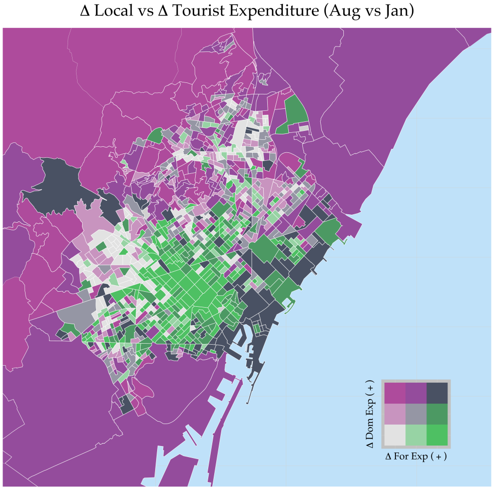
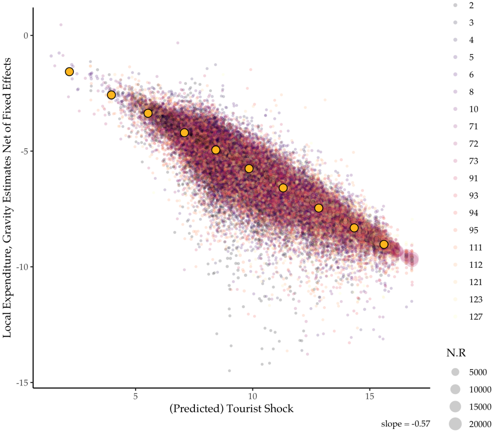
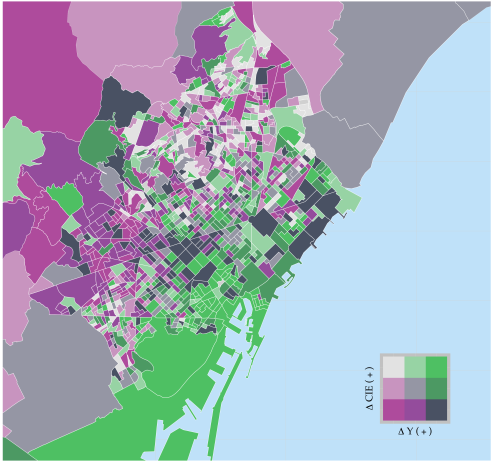
# Fact 3: Tourist spending affects local's spending

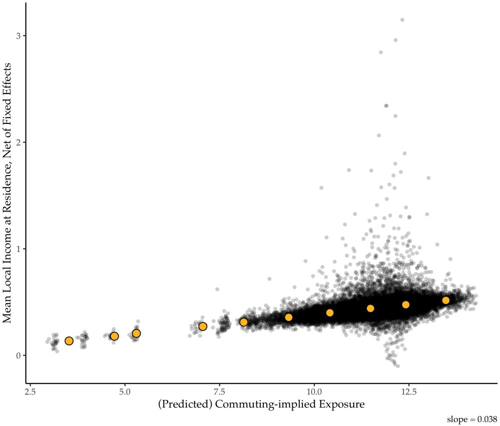


# Fact 3: Tourist spending affects local's incomes

Δ Income vs Δ Commuting Impl Exposure (Aug vs Jan)



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# Empirics

- From Theory to Estimation
- Identification
- Results

# From Theory to Estimation

- Welfare Formula

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- Estimates of key elasticities: $\left\{ \frac{\partial \ln p_i}{\partial \ln E_i^T}, \frac{\partial \ln w_i}{\partial \ln E_i^T} \right\}_{i=1}^{N}$

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- **Challenges**
  - $p_{it}$ includes non-pecuniary effects
  - our data: income $v_{nt}$, not wages $w_{it}$
  - $\ln E_{it}$ not exogenous (everyone likes the beach)

# From Theory to Estimation: Step 1

- Recovering amenity-adjusted prices
  - From CES preferences
  - $\delta_{it}$ is the destination fixed effect of a gravity regression:

$$\ln X_{nit} = \ln \delta_{nt} + \ln \delta_{it} + \beta^{dist} \ln travel\_time_{nit} + \varepsilon_{nit}$$

  - PPML estimated
  - Including both prices and non-pecuniary effects of tourism

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  - Including both prices and non-pecuniary effects of tourism

- Price Regressions (Average Treatment Effect)

$$\ln \delta_{it} = \alpha + \beta^{p} \times \ln E^{T}_{it} + \epsilon_{it}$$

# From Theory to Estimation: Step 1

- Tourist shock at residential level:
  - **Commuting implied exposure** measures impact of tourism on income

$$\ln \mathrm{CiE}^{T}_{ntm} = \sum_{i} c_{ni} \times \ln E^{T}_{itm}$$

  - Derived from income maximization problem Derivations

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$$\ln v_{nt} = \alpha + \beta^w \times \ln \text{CiE}^T_{ntm} + \epsilon_{it}$$

# From Theory to Estimation: Step 1

- Income & Price Regressions (Average Treatment Effect)

$$\ln v_{nt} = \alpha + \beta^{w} \times \ln \mathrm{CiE}^{T}_{ntm} + \epsilon_{it}$$

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$$\ln \delta_{it} = \alpha + \beta^{p} \times \ln E^{T}_{it} + \epsilon_{it}$$

- **Challenge**
  - Does not take heterog. into account when calculating welfare (Aggregation bias)

# From Theory to Estimation: Step 2

- Income & Price Regressions (Heterogeneous Treatment Effect)

$$\ln v_{nt} = \alpha + \beta^{w} \times \ln \mathrm{CiE}^{T}_{ntm} + \beta^{w,het} \times \ln \mathrm{CiE}^{T}_{ntm} \left(\eta^{0}_{itm}\right) + \epsilon_{it}$$

$$\ln \delta_{it} = \alpha + \beta^{p} \times \ln E^{T}_{it} + \beta^{p,het} \times \eta^{0}_{itm} \times \ln E^{T}_{it} + \epsilon_{it}$$

- Variables
  - $\eta^{0}_{itm} = E^{T}_{i} / y_{i}$ is the direct effect

# From Theory to Estimation: Step 2

- Income & Price Regressions (Heterogeneous Treatment Effect)

$$\ln v_{nt} = \alpha + \beta^{w} \times \ln \mathrm{CiE}^{T}_{ntm} + \beta^{w,het} \times \ln \mathrm{CiE}^{T}_{ntm}\left(\eta^{0}_{itm}\right) + \epsilon_{it}$$

$$\ln \delta_{it} = \alpha + \beta^{p} \times \ln E^{T}_{it} + \beta^{p,het} \times \eta^{0}_{itm} \times \ln E^{T}_{it} + \epsilon_{it}$$

- **Challenge**
  - Abstracts from GE spillover effects (SUTVA violation)

# From Theory to Estimation: Step 3

- Income & Price Regressions (HTE and Controlling for GE Spillovers)

$$\ln v_{nt} = \alpha + \beta^{w} \times \ln \text{CiE}^{T}_{ntm} + \beta^{w,het} \times \ln \text{CiE}^{T}_{ntm}\left(\eta^{0}_{itm}\right) + \epsilon_{it}$$

$$\ln \delta_{it} = \alpha + \beta^{p} \times \ln E^{T}_{it} + \beta^{p,het} \times \eta^{0}_{itm} \times \ln E^{T}_{it} + \beta^{p,GE} \times \eta^{0,Res}_{itm} \times \log E^{T,GE}_{itm} + \epsilon_{it}$$

- Variables
  - $\ln \text{E}^{T,GE}_{ntm}\left(\eta^{0}_{itm}\right) = \sum_{n} s_{ni} \times \ln \widehat{\text{CiE}^{T}_{ntm}}\left(\eta^{0}_{itm}\right)$ captures (first-degree) GE spillovers

# Identification: Shift-Share IV from Het Tourist Pref

- **Challenge:** Unobserved changes in attractiveness/productivity of a location
  - Induces comovement between residential expenditure and tourist expenditure
  - ...or residential income and tourist expenditure
  - ...or measurement error in independent variable (income proxy)

# Identification: Shift-Share IV from Het Tourist Pref

- **Our Strategy:** Shift-share IV from Heterogeneous Tourist Preferences
  - Total tourist expenditure is given by:

$$B_{it}^{T} = \sum_{g \in T} s_{git}^{0} \times E_{gt}^{T}$$

  - Shares $s_{git}^{0}$ capture spatial preferences for group $g$ in **baseline**
  - Shifts from changes in group-specific expenditures ($E_{gt}^{T}$)
    - Leave-own-location-out
  - Can be derived from non-parametric tourist demand Derivations
  - With FE identification comes from unanticipated changes in Tourist expenditures

First Stage

# Estimation Results

# Income Regressions: Average and Heterogeneous Effects

- Recover average treatment effects

$$\ln v_{nmt} = \gamma_i + \gamma_m + \gamma_t + \beta^w \times \ln \mathrm{CiE}^T_{ntm} + \epsilon_{imt},$$

- Recover heterogeneous treatment effects

$$\ln v_{nmt} = \gamma_i + \gamma_m + \gamma_t + \beta^w \times \ln \mathrm{CiE}^T_{ntm} + \beta^{w,het} \times \ln \mathrm{CiE}^T_{ntm} \left(\eta^0_{itm}\right) + \epsilon_{imt},$$

- Variables
  - $\ln v_{nmt}$ is income at residential tile and is regressed on:

$$\ln \mathrm{CiE}^T_{ntm} = \sum_i c_{ni} \times \ln E^T_{itm}$$

# Income Regressions: Average and Heterogeneous Effects

| Dependent Variable: | ln Income (Mean) | | | | | |
|---|---|---|---|---|---|---|
| | Cell | Lunch | Cell Phone | | Lunchtime | |
| | OLS | | IV - 2017 Low Season | | IV - 2017 Low Season | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| ln $\text{CiE}_{nt}$ | 0.012 | 0.006 | 0.035 | 0.008 | 0.040** | -0.009 |
| | (0.012) | (0.004) | (0.025) | (0.037) | (0.018) | (0.025) |
| $\eta^0_{it} \times \ln \widehat{\text{CiE}}_{nt}(\eta^0_{it})$ | | | | 0.046 | | 0.092*** |
| | | | | (0.033) | | (0.027) |
| *Fixed-effects* | | | | | | |
| Location | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Fit statistics* | | | | | | |
| Observations | 1,776 | 26,472 | 1,776 | 1,776 | 26,472 | 26,472 |
| Adjusted $R^2$ | 0.93 | 0.888 | 0.93 | 0.93 | 0.888 | 0.888 |
| $F$-test = $t^2$ (1st Stage) | | | 142.8 | 142.8 | 927.0 | 927.0 |

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

ATE Results (Details) HTE Results (Details)

# Price Regressions: Step 1

- Recover average treatment effects

$$\ln \delta_{ismt} = \gamma_{tms} + \gamma_{is} + \gamma_{ist} + \gamma_{ism} + \beta^{p} \times \log E^{T}_{itm} + \epsilon_{ismt},$$

- Variables
  - $\delta_{ismt}$ is destination FE from PPML specification on travel time
  - Binscatter Plot Gravity Results

# Price Regressions: Step 1

| Dependent Variable: | Residents Expenditure (Gravity): $\delta^R_{ist}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | OLS | | | IV - Ref: 2017 Average | | | IV - Ref: 2017 Low Season | | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Variables* | | | | | | | | | |
| Tourists Expenditure: $\ln E^T_{it}$ | 0.159*** | 0.152*** | 0.091*** | -0.437*** | -0.477*** | -0.576*** | -0.469*** | -0.512*** | -0.668*** |
| | (0.011) | (0.014) | (0.010) | (0.096) | (0.108) | (0.189) | (0.100) | (0.111) | (0.223) |
| *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 | 526,080 | 526,080 | 526,080 |
| Adjusted $R^2$ | 0.992 | 0.993 | 0.994 | 0.99 | 0.991 | 0.993 | 0.99 | 0.991 | 0.992 |
| $F$-test = $t^2$ (1st Stage) | | | | 145.4 | 138.2 | 38.4 | 153.3 | 148.7 | 30.7 |

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

Binscatter Plots

# Price Regressions: Step 2 and 3

- Recover heterogeneous treatment effects

$$\ln \delta_{ismt} = \gamma_{tms} + \gamma_{is} + \gamma_{ist} + \gamma_{ism} + \beta^{p,het} \times \eta^{0}_{itm} \times \log E^{T}_{itm} + \beta^{p,GE} \times \eta^{0,Res}_{itm} \times \log E^{T,GE}_{itm} + \epsilon_{ismt}$$

- Variables
  - $\eta^{0,Res}_{itm} = E^{R}_{i}/y_{i}$ is the importance of residential expenditures in a tile
  - (first-order) GE spillover effect is approximated by:

$$\ln \mathrm{E}^{T,GE}_{ntm}\left(\eta^{0}_{itm}\right) = \sum_{n} s_{ni} \times \ln \widehat{\mathrm{CiE}^{T}_{ntm}}\left(\eta^{0}_{itm}\right)$$

# Price Regressions: Step 2 and 3

| Dependent Variable: | $\delta^R_{ist}$ | | | | | |
|---|---|---|---|---|---|---|
| | IV - Ref: 2017 Average | | | IV - Ref: 2017 Low Season | | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| $\widehat{\ln E^T_{it}}$ | 0.019 | -0.029 | -0.059 | 0.011 | -0.037 | -0.062 |
| | (0.059) | (0.059) | (0.060) | (0.064) | (0.064) | (0.065) |
| $\widehat{\ln E^T_{it}} \times \eta^0_{it}$ | -0.523*** | -0.467*** | -0.357*** | -0.628*** | -0.555*** | -0.448*** |
| | (0.087) | (0.087) | (0.096) | (0.091) | (0.091) | (0.102) |
| $\widehat{\ln E^{GE}_{it}}(\bar{\eta}^0_i)$ | | -0.004*** | -0.009*** | | -0.005*** | -0.009*** |
| | | (0.0005) | (0.002) | | (0.0005) | (0.002) |
| $\widehat{\ln E^{GE}_{it}}(\bar{\eta}^0_i) \times \bar{\eta}^{0,Res}_i$ | | | 0.007*** | | | 0.006** |
| | | | (0.003) | | | (0.003) |
| *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 | 524,160 | 524,160 | 524,160 |
| Adjusted $R^2$ | 0.975 | 0.975 | 0.975 | 0.975 | 0.975 | 0.975 |

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

Group Estimates | Rental Rate Estimates

# Outline of Talk

A General Methodology for (small) Urban Shocks

Intra-city Patterns of Consumption & Income

Empirical Strategy and Identification

**Welfare Effects Across the City**

Comparison with a Quantitative Model

Conclusion

# Is tourism good for the locals (on average)?

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

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

- Average Welfare effects (Low/High Season)
  - Implies net welfare deterioration of 5pc

- Caveats
  - Aggregation Bias
  - SUTVA violation

Imputations

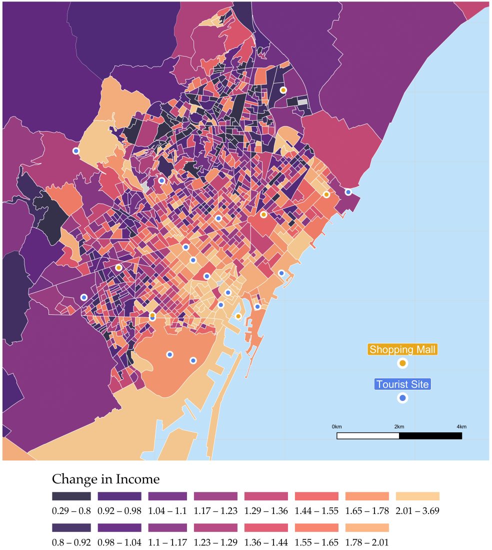
# Is tourism good for the locals?

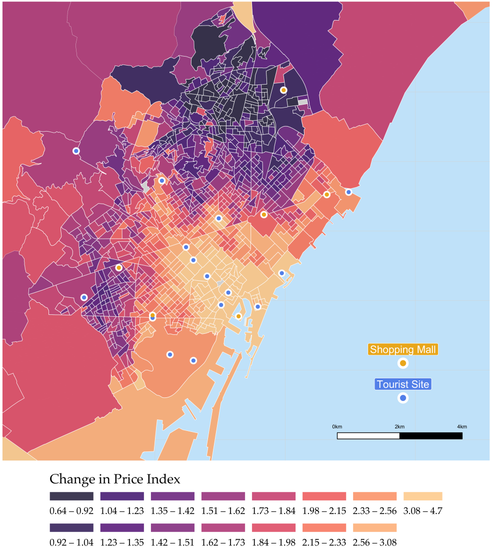
- Welfare Formula

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

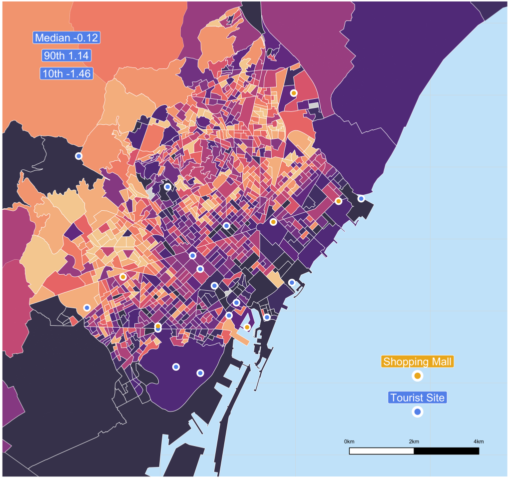
- $s_{ni}$ use baseline averages in 2017
- $c_{ni}$ only one cross-section available
- Predict income and price changes from January to August

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



# Welfare Effects




Change in Welfare

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| -6.15 – -1.73 | -1.28 – -0.97 | -0.75 – -0.58 | -0.38 – -0.22 | -0.05 – 0.08 | 0.22 – 0.42 | 0.66 – 0.93 | 1.43 – 8.29 |
| -1.73 – -1.28 | -0.97 – -0.75 | -0.58 – -0.38 | -0.22 – -0.05 | 0.08 – 0.22 | 0.42 – 0.66 | 0.93 – 1.43 | |

# Outline of Talk

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Conclusion

# Comparison to Quantitative Model

- Demand

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

- Wage Aggregator ($\epsilon < 0$)

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

- Production with Specific Factors

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

# Equilibrium

- Market Clearing Condition

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

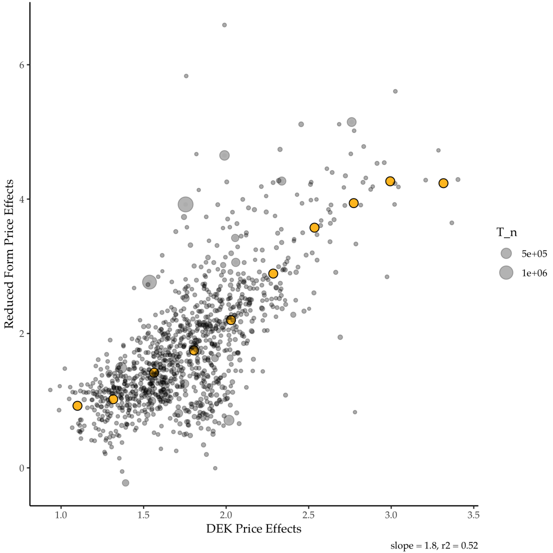
- Labor Market Clearing

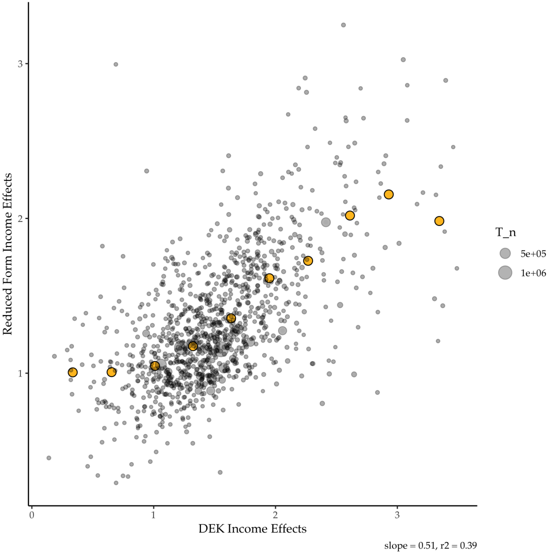
$$w_i \ell_i = \sum_{s=0}^{S} \theta_s^\ell \sum_{n=1}^{N} s_{nis} v_n + \sum_{s=0}^{S} \theta_s^\ell \sum_{g=1}^{G} s_{gis} E_g^T$$

- Disposable Income

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

# Price and Income Predictions highly correlated with DEK Results



# Price Regressions Redux

| Dependent Variable: | $\delta^R_{ist}$ | | | |
|---|---|---|---|---|
| | IV - Ref: 2017 Average | | | |
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| $\widehat{\ln E^T_{it}}$ | 0.011 | 2.63 | -0.062 | 4.49 |
| | (0.064) | (4.61) | (0.065) | (4.61) |
| $\widehat{\ln E^T_{it}} \times \eta^0_{it}$ | -0.628*** | -0.541*** | -0.448*** | -0.294 |
| | (0.091) | (0.179) | (0.102) | (0.186) |
| $\widehat{\ln E^T_{it}} \times \widehat{p}^{DEK}_i$ | | -2.58 | | -4.49 |
| | | (4.54) | | (4.55) |
| $\widehat{\ln E^{GE}_{it}}(\bar{\eta}^0_i)$ | | | -0.009*** | -0.009*** |
| | | | (0.002) | (0.002) |
| $\widehat{\ln E^{GE}_{it}}(\bar{\eta}^0_i) \times \bar{\eta}^{0,Res}_i$ | | | 0.006** | 0.006** |
| | | | (0.003) | (0.003) |
| *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 | 524,160 |
| Adjusted $R^2$ | 0.975 | 0.975 | 0.975 | 0.975 |

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

Income Regressions Redux

# Outline of Talk

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**Conclusion**

# Conclusion: Estimating the welfare impacts of an urban shock

- Option A: Quantitative model
  - (+) Incorporates full GE structure of the city
  - (-) Relies on strong parameterizations

- Option B: Average treatment effects
  - (+) Robust to model mis-specification
  - (-) Ignores heterogeneity, GE spillovers (SUTVA likely violated).

- Option C: A hybrid approach.
  - (+) Incorporates heterogeneity, (short-run) GE spillovers
  - (+) With a minimal set of model assumptions.

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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,

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

# 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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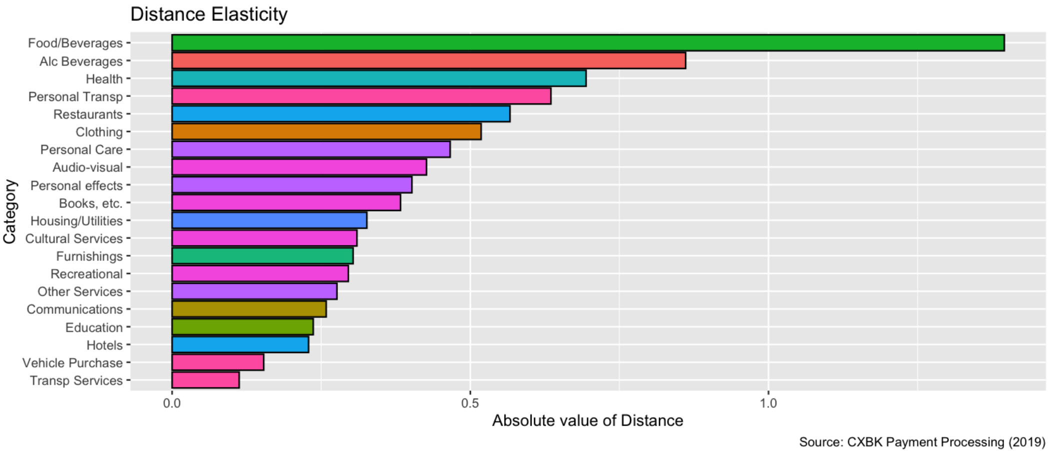
# Distance Coefficient for Gravity by Sector

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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*

back

# 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* | | | | | | | | |
| $\widehat{\log E^T_{it}}$ | 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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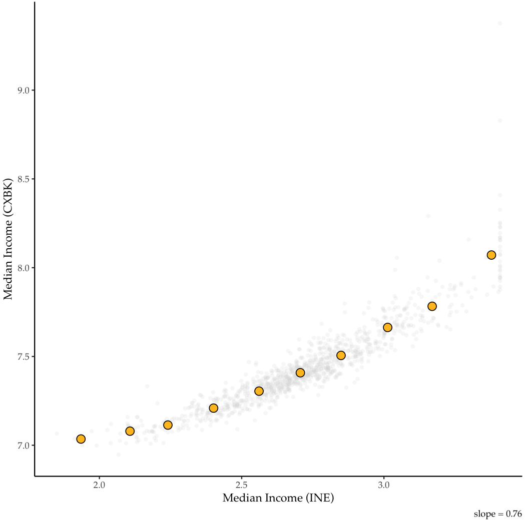
# Income Data: Comparison with Administrative Data

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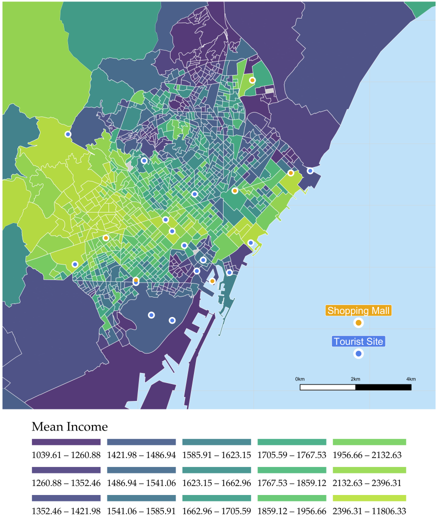
# Income Distribution across Barcelona

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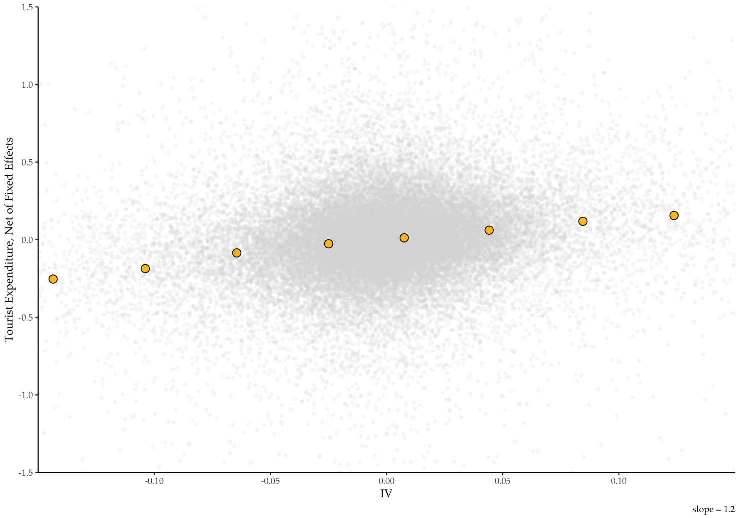
# Shift Share: First Stage

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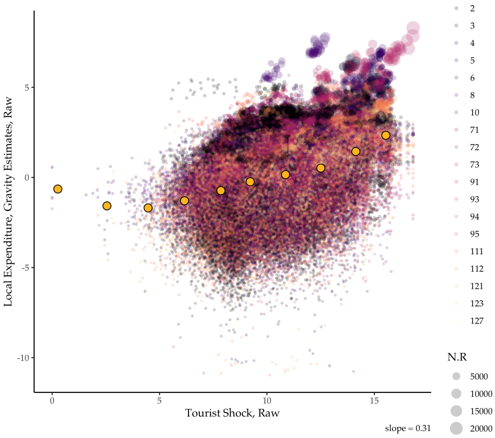
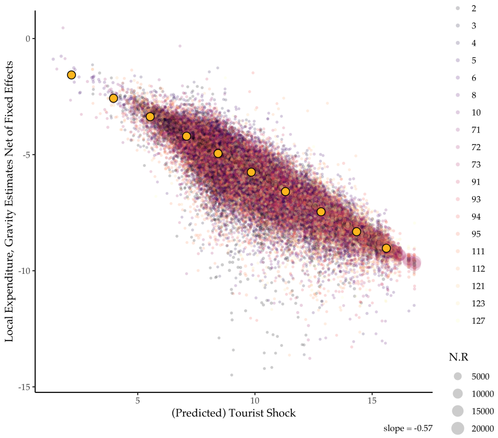
# Price Regressions: Raw vs 2SLS

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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*

back

# 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

back

# Income Regressions: Step 1

| Dependent Variable: | ln Income (Mean) | | | | | |
|---|---|---|---|---|---|---|
| | Lunch | Cell | Cell Phone | | Lunchtime | |
| | OLS | | IV - 2017 Average | IV - 2017 Low Season | IV - 2017 Average | IV - 2017 Low Season |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| ln $MA_{nt}$ | 0.006 | 0.012 | 0.032 | 0.035 | 0.038*** | 0.040** |
| | (0.004) | (0.012) | (0.021) | (0.025) | (0.015) | (0.018) |
| *Fixed-effects* | | | | | | |
| Location | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Fit statistics* | | | | | | |
| Observations | 26,472 | 1,776 | 1,776 | 1,776 | 26,472 | 26,472 |
| Adjusted $R^2$ | 0.888 | 0.93 | 0.93 | 0.93 | 0.888 | 0.888 |
| $F$-test = $t^2$ (1st Stage) | | | 204.5 | 142.8 | 1,267.2 | 927.0 |

*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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# Income Regressions: Step 2

| Dependent Variable: | ln Income (Mean) | | | | | |
|---|---|---|---|---|---|---|
| | Cell | Lunch | Cell Phone | | Lunchtime | |
| | OLS | | IV - 2017 Average | IV - 2017 Low Season | IV - 2017 Average | IV - 2017 Low Season |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| ln $\text{CiE}_{nt}$ | 0.012 | 0.006 | 0.007 | 0.008 | -0.005 | -0.009 |
| | (0.012) | (0.004) | (0.029) | (0.037) | (0.021) | (0.025) |
| ln $\widehat{\text{CiE}}_{nt}(\eta^0_{it})$ | | | 0.045 | 0.046 | 0.086*** | 0.092*** |
| | | | (0.030) | (0.033) | (0.027) | (0.027) |
| *Fixed-effects* | | | | | | |
| Location | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| *Fit statistics* | | | | | | |
| Observations | 1,776 | 26,472 | 1,776 | 1,776 | 26,472 | 26,472 |
| Adjusted $R^2$ | 0.93 | 0.888 | 0.93 | 0.93 | 0.888 | 0.888 |
| $F$-test = $t^2$ (1st Stage) | | | 204.5 | 142.8 | 1,267.2 | 927.0 |

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

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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 |
|---|---|---|
| $\beta_s$ | $0.65 \;\; \forall s$ | labor share of income |
| $\sigma_s$ | $4 \;\; \forall s$ | elasticity of substitution (within sectors) |
| $\eta$ | $1.5$ | elasticity of substitution (between sectors) |
| $\theta$ | $1.5$ | labor dispersion $(1 - \epsilon)$ |
| $\gamma$ | $[0, 0, 0, 0]$ | 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,

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

# 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: | $\delta^{R}_{ist}$ | $\delta^{T.Dom}_{ist}$ | $\delta^{T.For}_{ist}$ | $\delta^{R}_{ist}$ | $\delta^{T.Dom}_{ist}$ | $\delta^{T.For}_{ist}$ |
|---|---|---|---|---|---|---|
| | 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

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

- Constraint

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

- Utility max. gives lagrangian

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

# CES Model Example of Simple Non-Parametric Model

- FOCs

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

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

- 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*

$$
\begin{aligned}
\frac{\alpha_{ni}}{\alpha_{nj}} &= \frac{p_{ni}^{\sigma}}{p_{nj}^{\sigma}} \frac{q_{ni}}{q_{nj}} \\
q_{nj} &= \frac{\alpha_{nj}}{\alpha_{ni}} \frac{p_{ni}^{\sigma}}{p_{nj}^{\sigma}} q_{ni}
\end{aligned}
$$

- $\times p_{nj}$

$$
\begin{aligned}
q_{nj} p_{nj} &= \frac{\alpha_{nj}}{\alpha_{ni}} \frac{p_{ni}^{\sigma}}{p_{nj}^{\sigma}} q_{ni} p_{nj} \\
q_{nj} p_{nj} &= \frac{1}{\alpha_{ni}} q_{ni} p_{ni}^{\sigma} \alpha_{nj} p_{nj}^{1-\sigma}
\end{aligned}
$$

# CES Model Example of Simple Non-Parametric Model

- $\sum_j$

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

- using FOC2 (BC)

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

- and demand for good $i$

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

# CES Model Example of Simple Non-Parametric Model

- We get indirect utility

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

- We can also express demand as total spending

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