Uncovering the Sources of Geographic Market Segmentation: Evidence from the EU and the US

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Measuring market integration

- **Geographic market integration**:
  - the unification of spatial units into larger interconnected markets
  - typically happens through reductions in:
    - **within-country frictions** e.g. improvements in transport infrastructure
    - **cross-border frictions** e.g. reductions in variable or fixed trade frictions

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  - between and within-country price differences: (Engel & Rogers, 1996; Goldberg & Knetter, 1997)
  - between and within-country trade shares: (McCallum, 1995; Santamaria et al., 2020)

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  - between and within-country trade shares: (McCallum, 1995; Santamaria et al., 2020)

- Both approaches have **conceptual issues**:
  - LOP-deviations ignore differences in product availability and fixed trade frictions
  - Trade shares do not map into trade frictions when consumer taste differs across countries.

Propose alternative approach

- **Contribution**: Detect cross-border market segmentation
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- Cross-country **scanner data** to measure prices and product availability + **two-step approach**:
  1. **Measurement**: estimate and decompose *regional cost-of-living differences*:

$$\text{P}^{kl} = \text{Price diff.}^{kl} + \text{Availability diff.}^{kl} + \text{Taste diff}^{kl}$$

  2. **Identification**: design *spatial differencing strategy* to
     - Isolate variation in between- and within-country variation in prices and availability
     - Under certain conditions this variation maps to the presence of variable and fixed trade frictions.

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- **Application**:
  - Detect cross-border market segmentation between EU countries
  - Compare that to potential cross-border market segmentation between US states.

EU countries are segmented, US states are not

Our results:

- **Cost-of-living** differences are
  - $\sim$ 2.5 times larger between *EU countries* compared to within.
  - Barely larger between *US States* compared to within.
  - A large part of these cost-of-living differences is driven by **taste differences**

Literature

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- For **US states**
  - Similar price and product availability differences between and within them.
  - $\hookrightarrow$ US States seem well integrated.
- For **European countries**
  - Significantly larger price and product availability differences between EU countries than within them.
  - Product availability differences are $\sim$ 3 times larger.
  - $\hookrightarrow$ Variable and fixed trade frictions still segment European countries.

Literature

DATA AND REDUCED FORM-EVIDENCE

Regional scanner data

- Household-level **scanner data** from 2010-2019:
  - **Europe**: Belgium, France, Germany, the Netherlands (Kantar + GfK) and the **USA** (Nielsen HomeScan)
  - Sample of households: $\sim$ 3,500 - 22,500 households per country-year
  - All household purchases in 68 FMCGs ($\sim$ 15% of CPI basket)

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- Spatial distribution of prices and product availability:
  - Common barcode system $\Longrightarrow$ **price and product availability**
  - GS1 barcode-firm link $\Longrightarrow$ **firm identifiers**
  - Household ZIPcodes $\Longrightarrow$ **Regions** ($>$ 80 NUTS2 regions + $>$ 150 DMA-States).

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- **Comparable** observed consumption behavior and firm size distributions across countries

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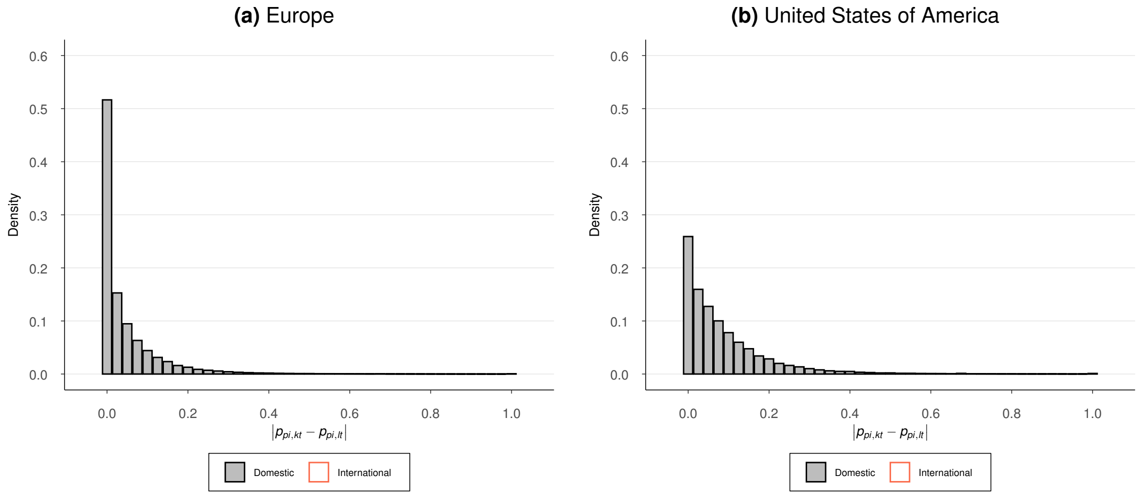

Figure 1: LOP deviations (transaction-weighted)

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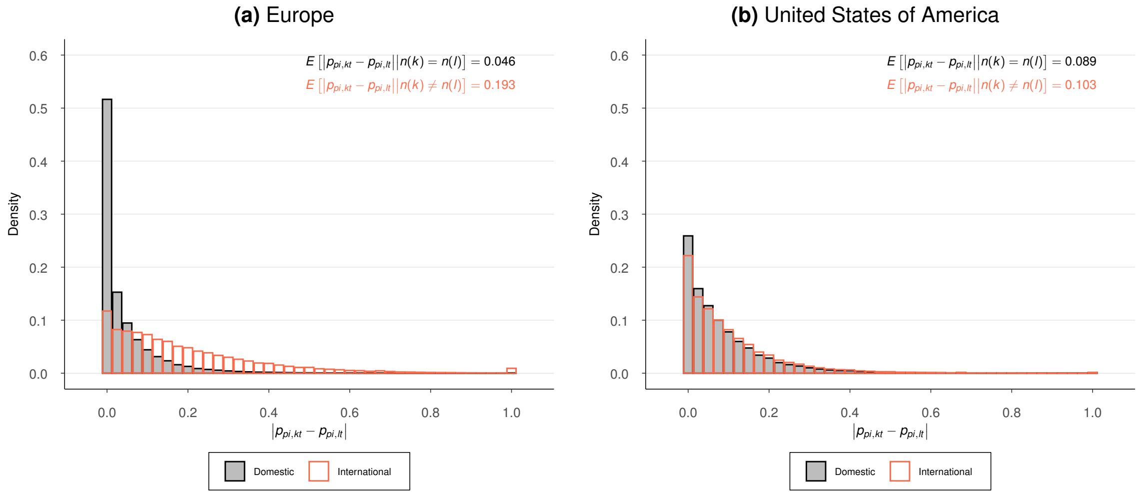

Figure 1: LOP deviations (transaction-weighted)

Construction | Unweighted | Branded and Private label | Branded | Within chains

... but so are differences in product availability, $1-\frac{\sum_{i\in\mathcal{B}_{p,lt}}\mathbb{1}\left(i\in\mathcal{B}_{p}^{kl}\right)}{\left|\mathcal{B}_{p,lt}\right|}$

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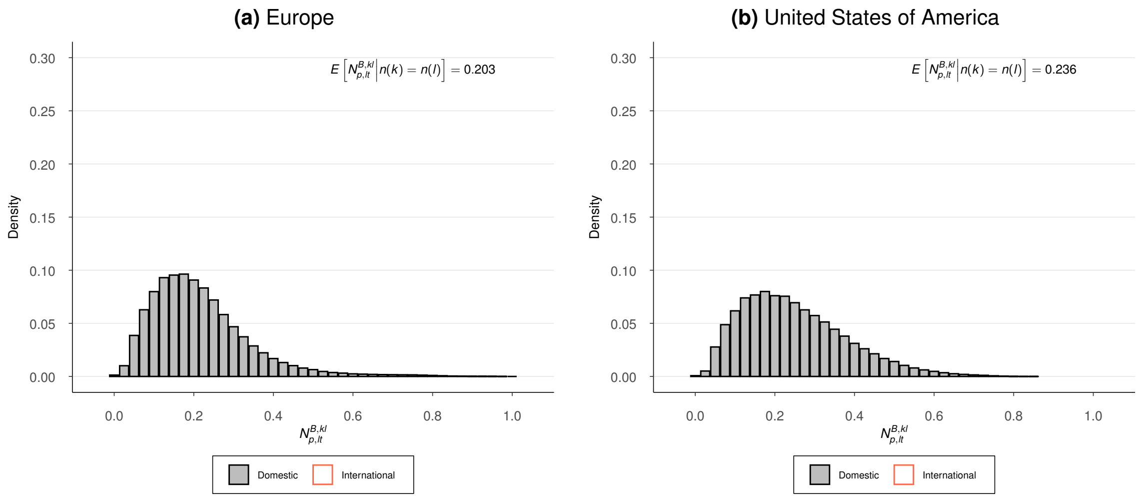

Figure 2: Differences in product availability: Variety-level (Numbers)

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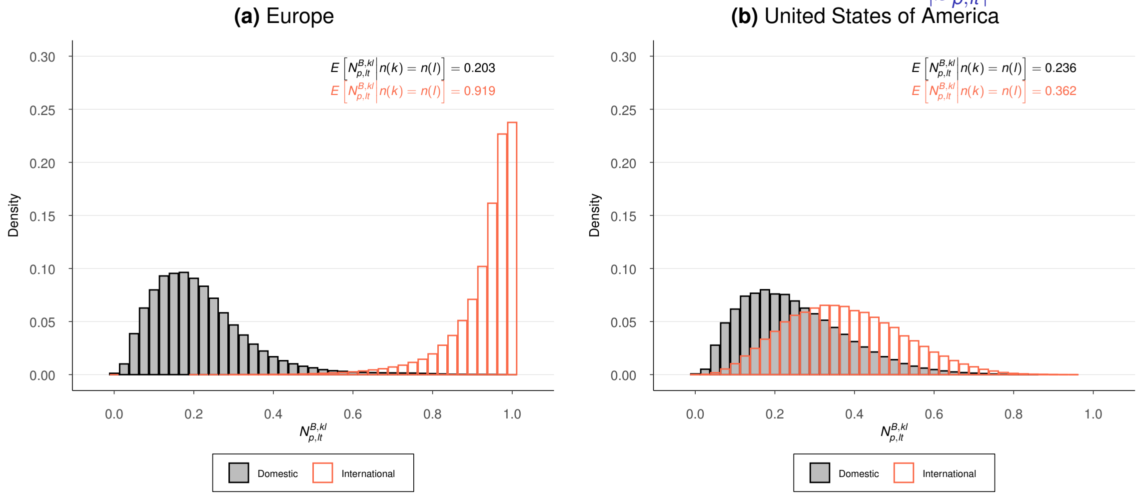

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Two-step approach

Step 1: Regional cost-of-living differences - ▸ Preferences ▸ First decomposition

Given nested CES-preferences + Taste normalization (à la Redding & Weinstein (2020)) yield:

$$\ln P^{kl}_{p,kt} - \ln P^{kl}_{p,lt} = \underbrace{\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\left[\sum_{i\in\Omega^{kl}_{pf}} \omega^{kl}_{pfi,t} \ln\left(\frac{P_{pfi,kt}}{P_{pfi,lt}}\right)\right]}_{\text{Average price differences}(L^{kl}_{p,t})} + \underbrace{\frac{1}{\eta_p - 1}\ln\left(\frac{\lambda^{kl}_{p,kt}}{\lambda^{kl}_{p,lt}}\right) + \frac{1}{\sigma_p - 1}\frac{1}{N^{kl}_p}\sum_{f\in\Omega^{kl}_p}\ln\left(\frac{\lambda^{kl}_{pf,kt}}{\lambda^{kl}_{pf,lt}}\right)}_{\text{Differences in product availability}(\Lambda^{kl}_{p,t})}$$

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Step 2: Spatial differencing strategy - ▸ Market structure

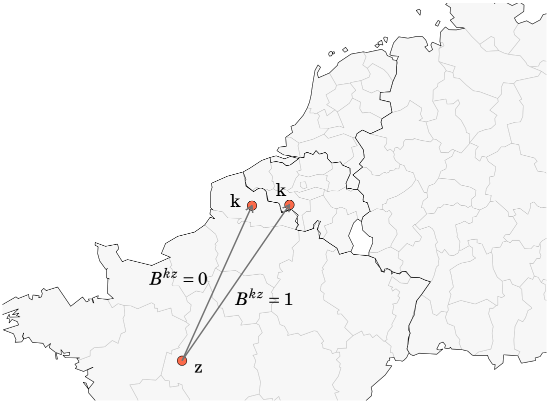
Detecting cross-border segmentation requires controlling for domestic trade frictions.

- Scanner data does not have production location $\Longrightarrow$ domestic trade frictions are unobserved

$\hookrightarrow$ **Solution**: Compare absolute differences between international and domestic region pairs

Step 2: Observed transport costs: "Simple differences"

$$\mathbb{E}\left[Y^{kz}(1) - Y^{kz}(0) \middle| B^{kz} = 1, \boldsymbol{X}^{kz} = \boldsymbol{x}\right] \qquad \text{where } Y^{lz} = \begin{cases} Y^{kz}(1) & \text{if } B^{kz} = 1, \\ Y^{kz}(0) & \text{if } B^{kz} = 0, \end{cases}$$



Step 2: Unobserved transport costs: "Differences in absolute value"

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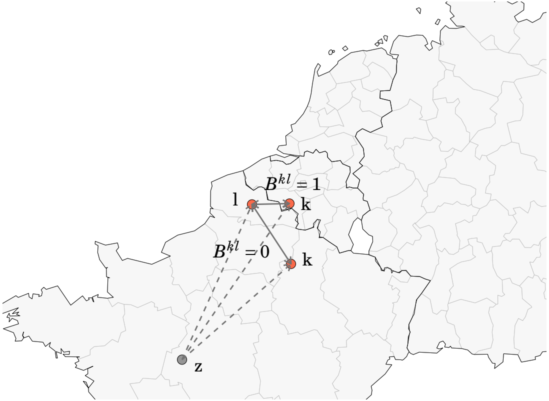

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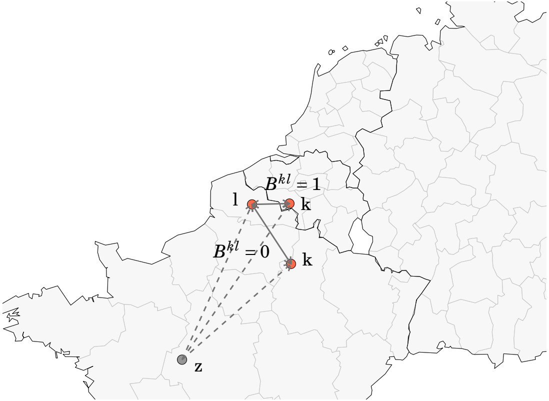

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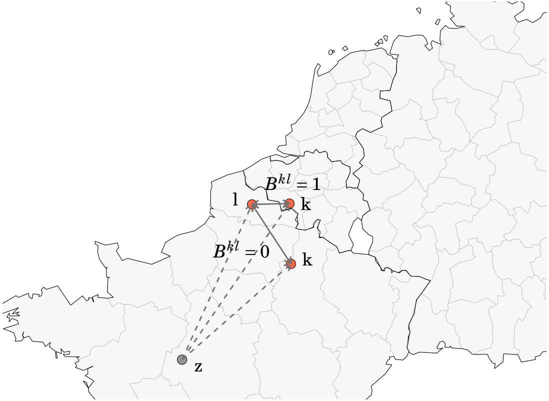

Step 2: Spatial differencing strategy - Market structure

Identifying cross-border market segmentation requires controlling for transport costs:

- With scanner data, transport costs are unobserved
- **Spatial strategy**: Compare absolute differences between international and domestic region pairs:

$$\mathbb{E}\left[\left|Y^{kl}(1)\right| - \left|Y^{kl}(0)\right| \,\middle|\, B^{kl} = 1, \boldsymbol{X}^{kl} = 0\right]$$

Proposition (Detecting cross-border market segmentation)

Given

1. *Preferences with infinite choke prices (e.g. CES)*
2. *No diseconomies of scale*
3. *Frictionless domestic entry*

We have:

$$\tau_L \equiv \mathbb{E}\left[\left|L^{kl}_{p,t}(1)\right| - \left|L^{kl}_{p,t}(0)\right| \,\middle|\, B^{kl} = 1, \boldsymbol{X}^{l} = 0\right] > 0 \quad \Rightarrow \quad \exists\ \tau_{pfi,t} > 0$$

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Estimation Results

Detecting cross-border market segmentation - Estimation procedure

To implement the previous proposition, we take three steps:

1. Estimate **elasticities of substitution** σ_p and η_p
   - Variety-level elasticities: $\hat{\mathbb{E}}\left[\hat{\sigma_p}\right] = -2.77$ with $10\% - 90\% : [-4.77, -1.15]$ ▸ Strategy ▸ Results
   - Firm-level elasticities: $\hat{\mathbb{E}}\left[\hat{\eta_p}\right] = -3.10$ with $10\% - 90\% : [-4.84, -1.71]$ ▸ Results ▸ Results

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2. Compute $\ln \boldsymbol{P}^{ml}_{p,t} - \ln \boldsymbol{P}^{kl}_{p,t}$ for all region pairs ($\sim$ 3200 pairs):
   - Draw a sample of households with replacement in each region
   - Draw from $\hat{N}\left(\hat{\mathbb{E}}[\hat{\sigma_p}], \hat{\mathbb{V}}[\hat{\sigma_p}]\right)$ and $\hat{N}\left(\hat{\mathbb{E}}[\hat{\eta_p}], \hat{\mathbb{V}}[\hat{\eta_p}]\right)$
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   - Implement the structural decomposition into the three components.
3. For each bootstrap sample, find the set of "geographically close" region pairs $\mathcal{D}_\varepsilon \equiv \left\{(k,l) : B^{kl} = 1 \cap F\left(D\left(\boldsymbol{X}^{kl}\right)\right) \leq \varepsilon\right\}$ and compute

$$\hat{\tau}_{L,\varepsilon} \equiv \frac{1}{N} \sum_{(k,l)\in\mathcal{D}_\varepsilon} \left[|L^{kl}_{p,t}(1)| - |\hat{L}^{kl}_{p,t}(0)|\right], \qquad \hat{\tau}_{\Lambda,\varepsilon} \equiv \frac{1}{N} \sum_{(k,l)\in\mathcal{D}_\varepsilon} \left[|\Lambda^{kl}_{p,t}(1)| - |\hat{\Lambda}^{kl}_{p,t}(0)|\right]$$

Detecting cross-border market segmentation

Table 1: Geographic market segmentation: Estimation results ($\varepsilon = 0.10$)

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.3787***	.3041***	.0967***	.2972***
	[.3548, .4114]	[.2866, .3276]	[.0953, .0977]	[.2768, .3259]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.26	.2372	.0125	.0427
Nr. treated	146	146	146	146
Nr. matched units	1	1	1	1
Nr. unique controls	81	81	81	81
Nr. obs	9,928	9,928	9,928	9,928
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0049*	.0092***	.0062***	.0145***
	[−.0008, .0098]	[.005, .0138]	[.0059, .0065]	[.0127, .0165]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4168	.356	.0241	.0926
Nr. treated	601	601	601	601
Nr. matched units	1	1	1	1
Nr. unique controls	98	98	98	98
Nr. obs	40,100	40,100	40,100	40,100

Notes: Block-bootstrapped standard errors on 50 iterations at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

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	[.3548, .4114]	[.2866, .3276]	[.0953, .0977]	[.2768, .3259]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.26	.2372	.0125	.0427
Nr. treated	146	146	146	146
Nr. matched units	1	1	1	1
Nr. unique controls	81	81	81	81
Nr. obs	9,928	9,928	9,928	9,928
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0049*	.0092***	.0062***	.0145***
	[−.0008, .0098]	[.005, .0138]	[.0059, .0065]	[.0127, .0165]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4168	.356	.0241	.0926
Nr. treated	601	601	601	601
Nr. matched units	1	1	1	1
Nr. unique controls	98	98	98	98
Nr. obs	40,100	40,100	40,100	40,100

Notes: Block-bootstrapped standard errors on 50 iterations at the $p < 0.1^{*}$, $p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Detecting cross-border market segmentation

Table 1: Geographic market segmentation: Estimation results ($\varepsilon = 0.10$)

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
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Variance decomposition | $\varepsilon = 0.05$ | Nr controls = 3 | Markups | CES preferences | Alternative elasticities

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Placebo estimates - Price differences

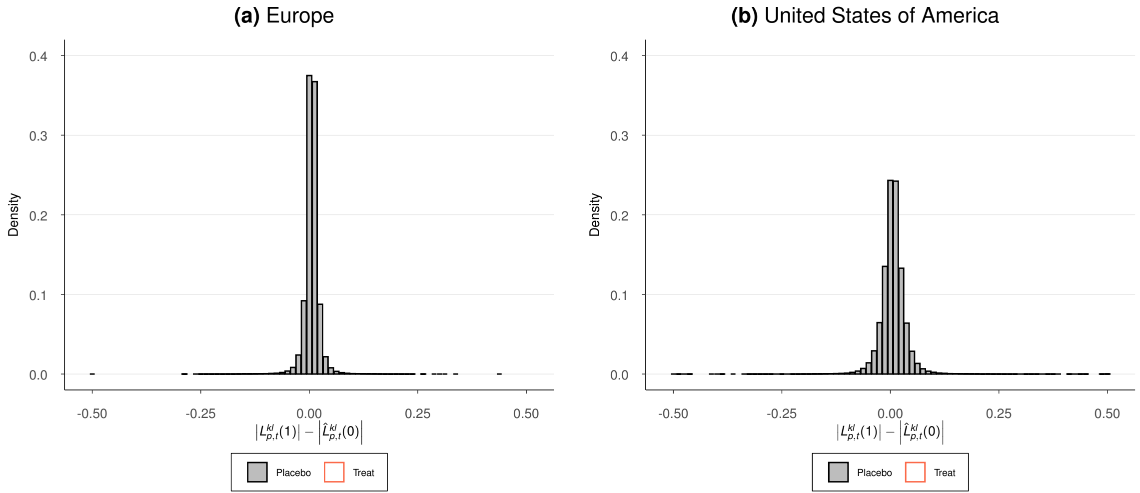


Figure 3: Price differences

Placebo estimates - Price differences

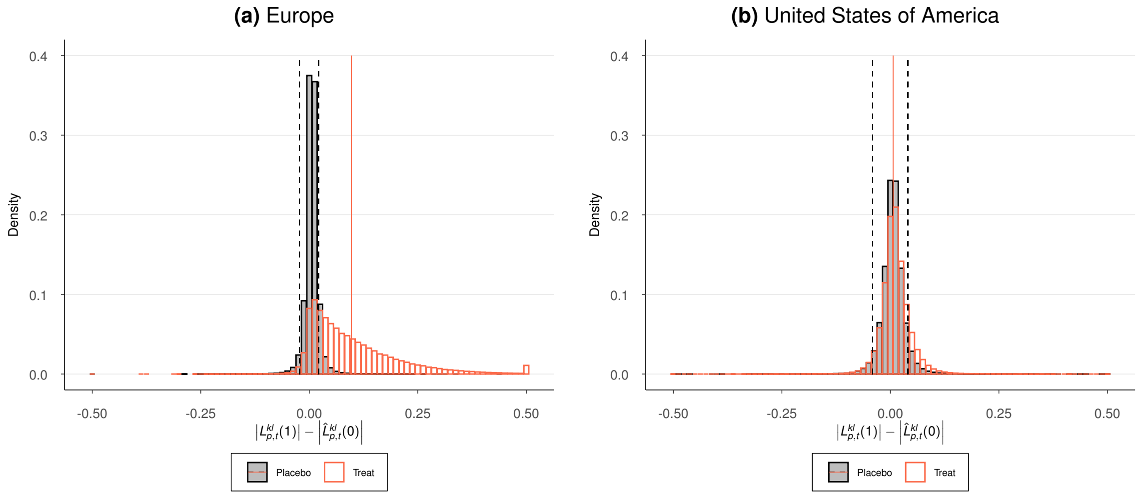


Figure 3: Price differences

Placebo estimates - Product availability differences

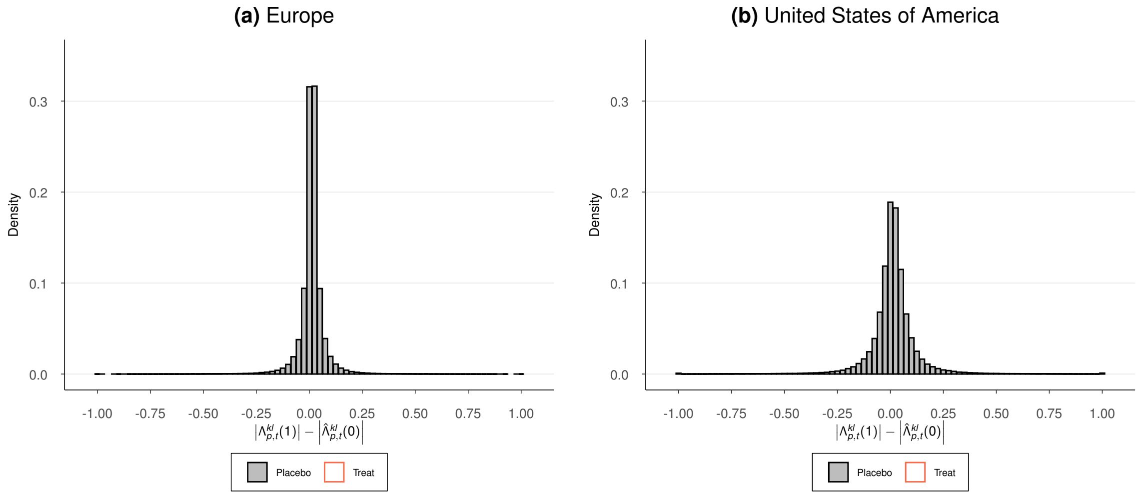


Figure 4: Differences in product availability

Placebo estimates - Product availability differences

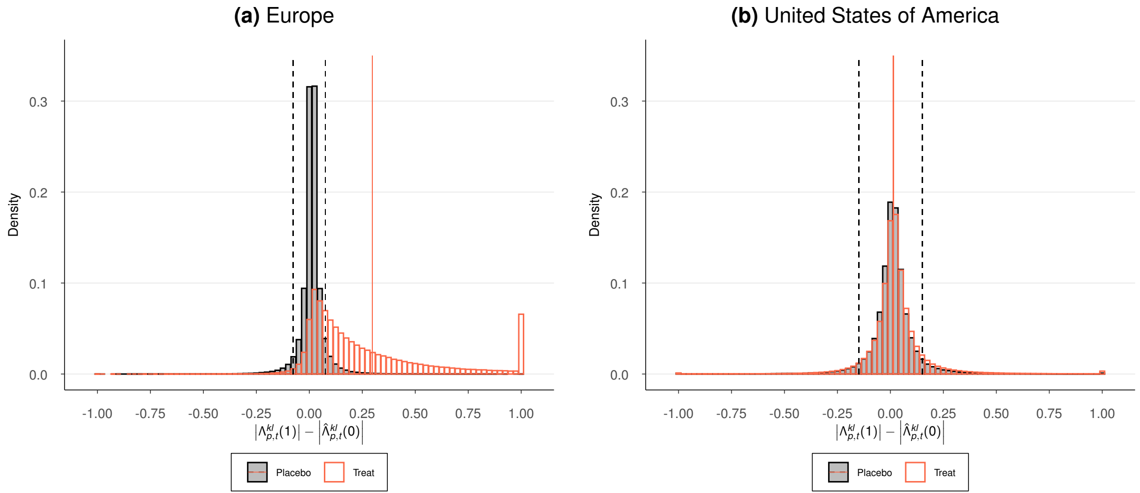


Figure 4: Differences in product availability

CONCLUSION

Conclusion

- Study **cross-border market segmentation** in final goods markets
- We propose an **alternative approach** in which
  - We account for both LOP deviations and choice set differences as manifestations of cross-border geographic market segmentation
  - We control for taste differences for common varieties
- Main findings:
  - **Controlling for taste differences** is quantitatively important
  - Cannot reject that **US states** are geographically integrated.
  - **European final goods markets** remain segmented across borders with most variation accounted for by differences in product availability

APPENDIX

Literature

- **Cost-of-living differences with CES**: Feenstra (1994); Broda & Weinstein (2006); Handbury & Weinstein (2015); Redding & Weinstein (2020); Feenstra et al. (2020); Argente et al. (2021); Cavallo et al. (2023)
  - *Literature*: Focus on differences over time, across countries or within countries
  - *This paper*: Combine differences across and within country $\Longrightarrow$ Cross-border market segmentation
- **LOP deviatons**: Engel & Rogers (1996), Gorodnichenko & Tesar (2009), **?**, Cavallo et al. (2014) and Beck et al. (2020)
  - *Literature*: Focused on price differences for a small set of available varieties
  - *This paper*: Add differences in product availability
- **Border effects in Trade**: McCallum (1995), Anderson & Wincoop (2003), Helpman et al. (2008) and Santamaria et al. (2020)
  - *Literature*: Strong assumptions on demand and market structure to map trade shares to trade costs
  - *This paper*: Empirically separate geographic market segmentation from differences in consumer taste

Data Sources

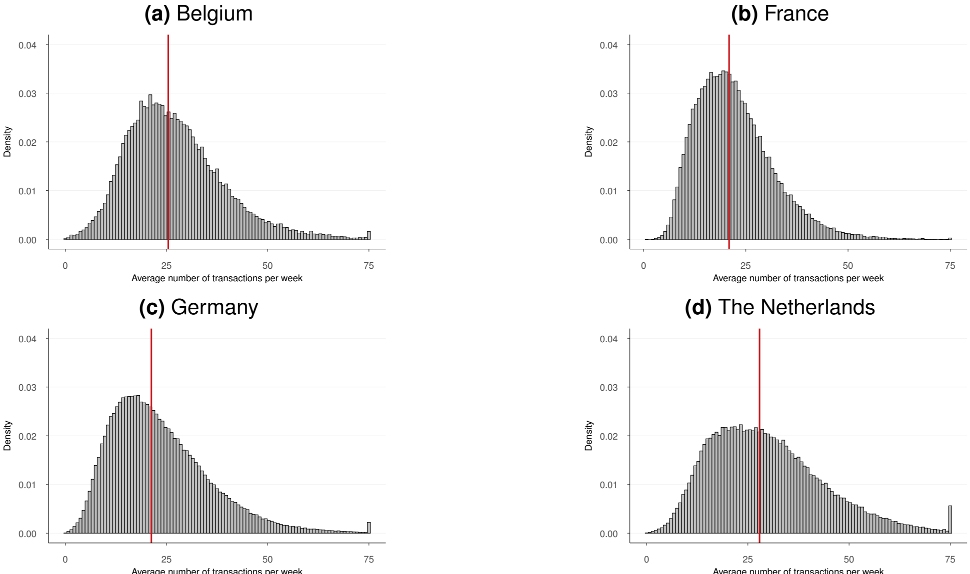
Back

- **Household-level scanner data** at country-household-barcode-chain-time level:
  - Belgium, France, Germany and the Netherlands
  - Sample of households: $\sim$ 3,500 - 22,500 households/year
  - Food and non-food FMGCs: 68 categories $\sim$ 15% of CPI
  - Universe of stores
  - Data from 2010 to 2019
- **Firm identifiers** obtained from GS1
  - Link barcodes to unique GS1 firm IDs
  - Identify barcodes supplied by common firms across countries
- **Geographic data** from Eurostat GISCO, EEA and US Geological Survey
  - Link household ZIP codes to NUTS2 regions
  - $>$ 80 NUTS2 region pairs.

Comparability across countries - Transactions

Back

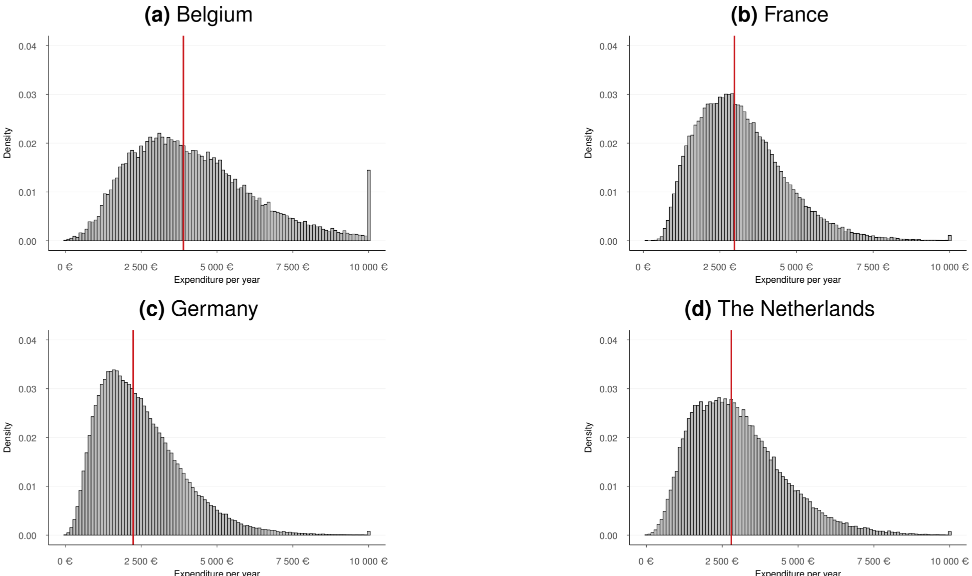
Figure 5: Purchases per week



Comparability across countries - Expenditure per year

Back

Figure 6: Expenditure per year



Comparability across countries - Firm size distribution

Back

Table 2: Size Distribution by number of UPCs

	Belgium			France		
Nr. UPCs	Nr. Firms	Bin share	St dev. UPC sales	Nr. Firms	Bin share	St dev. UPC sales
1	174	1.47	1.36	65	0.76	1.63
2-5	126	3.90	1.42	57	2.84	1.65
6-10	33	3.78	1.50	22	3.59	1.67
11-20	23	6.69	1.54	19	6.56	1.67
21-50	15	14.34	1.62	21	16.69	1.70
51-100	7	19.47	1.68	9	19.17	1.68
$\geq$ 100	7	56.50	1.83	9	56.50	1.74
	Germany			**Netherlands**		
Nr. UPCs	Nr. Firms	Bin share	St dev. UPC sales	Nr. Firms	Bin share	St dev. UPC sales
1	99	1.30	1.66	128	1.12	1.69
2-5	105	4.41	1.63	104	3.39	1.74
6-10	36	4.34	1.66	30	3.40	1.79
11-20	29	7.74	1.70	22	6.93	1.85
21-50	27	16.45	1.76	18	16.32	1.91
51-100	12	20.16	1.85	7	18.06	1.86
$\geq$ 100	10	52.16	1.95	9	58.02	1.94

Comparability across countries - Firm size distribution

Back

Table 3: Average Firm and UPC size

	Belgium				France			
	Mean	Median	$10^{th}\%$	$90^{th}\%$	Mean	Median	$10^{th}\%$	$90^{th}\%$
Nr. firms	300	262	102	545	199	166	75	377
Firm sales	1,272	1,029	503	2,436	5,169	4,452	1,868	9,208
Log firm sales	4	4	3	4	5	5	5	6
UPCs per firm	10	10	6	14	18	16	9	26
UPC sales	45	38	20	77	161	120	64	313

	Germany				Netherlands			
	Mean	Median	$10^{th}\%$	$90^{th}\%$	Mean	Median	$10^{th}\%$	$90^{th}\%$
Nr. firms	305	273	91	609	272	257	95	484
Firm sales	5,320	4,390	2,242	9,182	2,953	2,463	1,061	5,690
Log firm sales	6	6	5	6	4	4	4	5
UPCs per firm	15	13	8	23	11	11	6	16
UPC sales	216	177	90	362	109	87	40	219

Comparability across countries - Firm size distribution

Back

Table 4: Size distribution by Decile

	Belgium				France			
Decile	Decile mkt	Firm mkt	Mean UPCs	Median UPCs	Decile mkt	Firm mkt	Mean UPCs	Median UPCs
1	92.38	4.15	61.9	35.7	84.10	5.72	99.1	75.9
2	4.42	0.25	12.9	9.5	9.87	0.82	30.4	25.2
3	1.54	0.08	7.4	5.7	3.33	0.29	16.7	13.0
4	0.73	0.04	4.7	3.7	1.40	0.12	10.1	8.0
5	0.41	0.02	3.2	2.5	0.70	0.06	6.8	5.5
6	0.45	0.01	2.7	2.1	0.66	0.04	5.1	3.7
7	0.14	0.01	1.9	1.5	0.17	0.01	2.9	2.2
8	0.08	0.00	1.5	1.1	0.08	0.01	2.1	1.6
9	0.05	0.00	1.2	1.0	0.03	0.00	1.6	1.2
10	0.02	0.00	1.1	1.0	0.01	0.00	1.1	1.0
	Germany				Netherlands			
Decile	Decile mkt	Firm mkt	Mean UPCs	Median UPCs	Decile mkt	Firm mkt	Mean UPCs	Median UPCs
1	84.97	4.20	85.7	55.5	91.81	4.36	85.8	40.5
2	8.62	0.52	23.2	18.7	5.31	0.36	14.2	9.7
3	3.25	0.19	12.5	9.7	1.60	0.11	8.1	5.6
4	1.50	0.08	7.6	5.8	0.64	0.04	5.3	3.9
5	0.82	0.04	4.7	3.5	0.32	0.02	3.8	2.8
6	0.83	0.03	3.9	2.9	0.32	0.01	3.1	2.3
7	0.24	0.01	2.7	2.0	0.09	0.00	2.1	1.6
8	0.12	0.01	2.1	1.5	0.04	0.00	1.7	1.2
9	0.06	0.00	1.6	1.1	0.02	0.00	1.3	1.0
10	0.02	0.00	1.2	1.0	0.01	0.00	1.1	1.0

Price differences are large ... - Back

Three steps to compute a measure of LOP deviations:

1. Define the set of varieties, $\mathcal{B}_{lt}$, for region l at time t.
2. Define the set of common varieties, $\mathcal{B}^{kl}$, for regions k and l:

$$\mathcal{B}^{kl} \equiv \{i \quad | \quad \exists\ i \in \Omega_{lt} \cap \exists\ i \in \Omega_{kt}\}$$

3. Within region pair-time units, compute absolute LOP deviations:

$$\left|p_{pi,kt} - p_{pi,lt}\right|$$

Price differences are large ... - ▸ Back

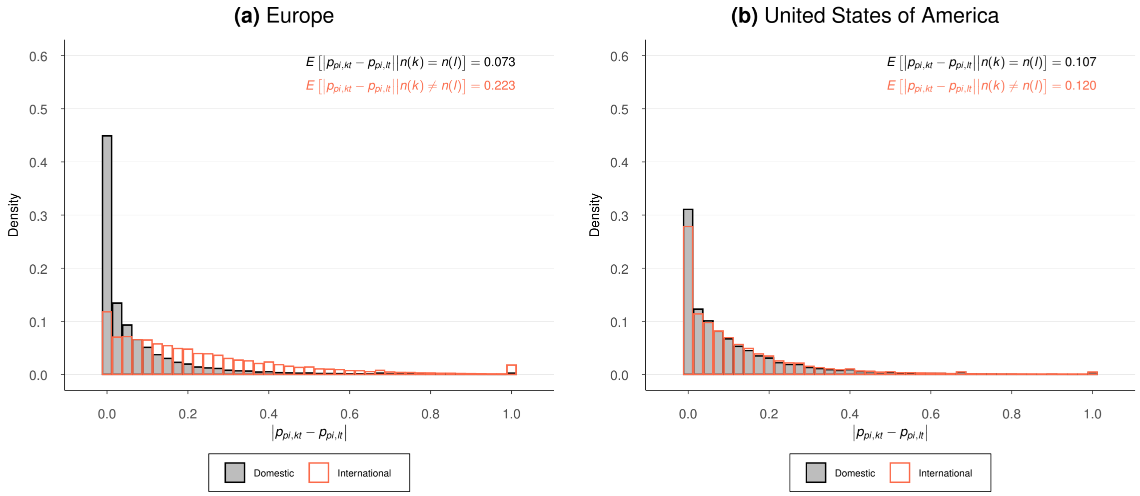


Figure 7: LOP deviations (Unweighted)

Price differences are large ... - Back

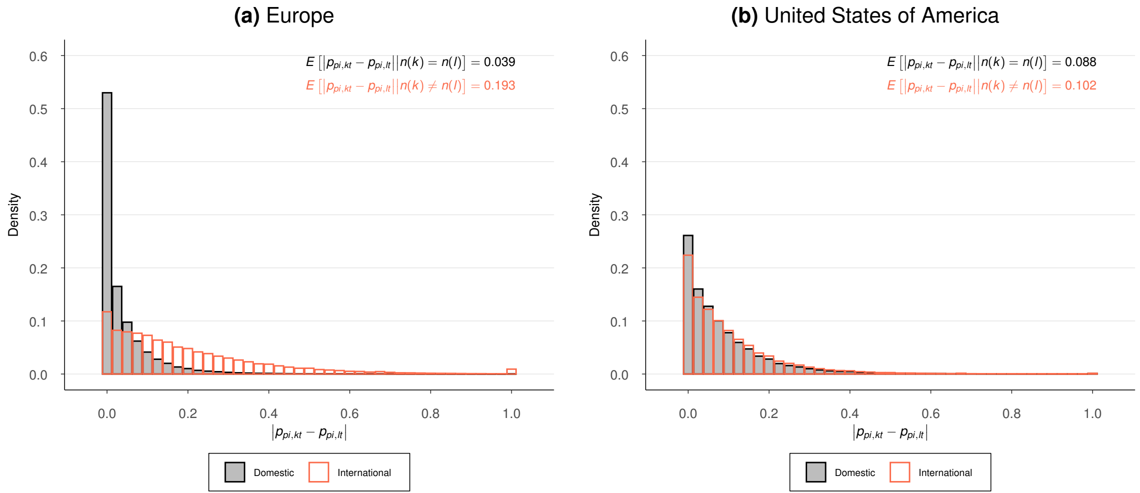


Figure 8: LOP deviations (Branded and Private label)

Price differences are large ... - Back

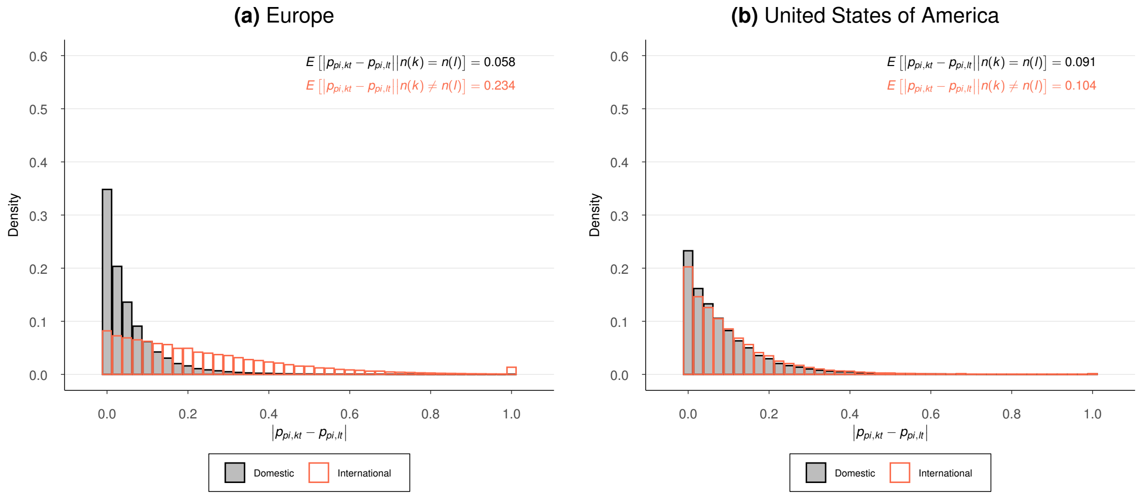


Figure 9: LOP deviations (Branded)

Price differences are large ... - Back

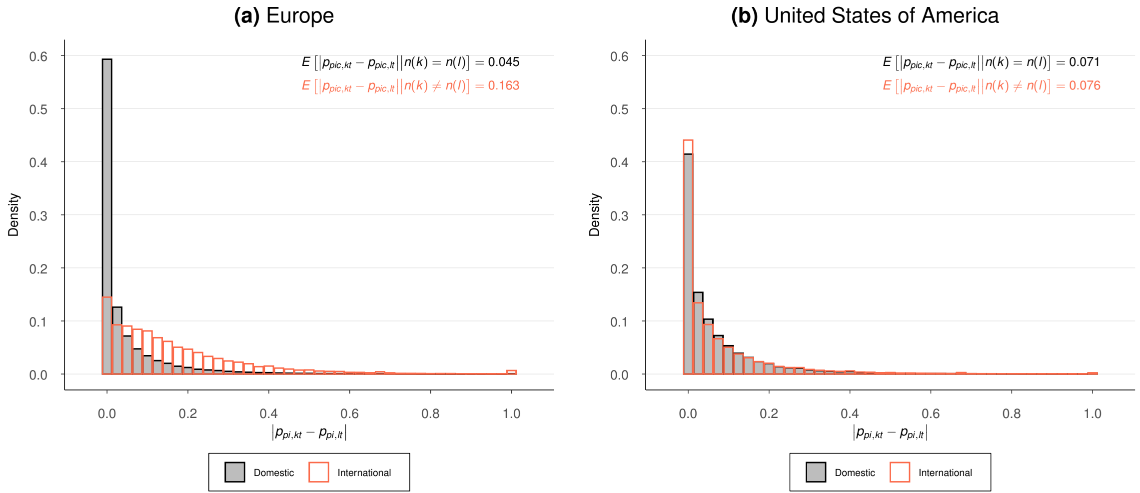


Figure 10: LOP deviations (Within chains)

.. but so are differences in product availability - Back

Three steps to compute differences in product availability

1. Consider again the set of varieties $\mathcal{B}_{lt}$ in region l
2. Consider again the set of common varieties, $\mathcal{B}^{kl}$, for regions k and l:
3. Within region pair-time units, compute the share on varieties which *not common*:

$$N_{p,t}^{B,kl} \equiv 1 - \frac{\sum_{i\in\mathcal{B}_{p,lt}} \mathbb{1}\left(i \in \mathcal{B}_p^{kl}\right)}{|\mathcal{B}_{p,lt}|}, \quad \lambda_{p,t}^{B,kl} \equiv 1 - \frac{\sum_{i\in\mathcal{B}_{p,lt}} E_{pfi,lt}\mathbb{1}\left(i \in \mathcal{B}_p^{p,kl}\right)}{\sum_{i\in\mathcal{B}_{p,lt}} E_{pfi,lt}}$$

... but so are differences in product availability - $1 - \frac{\sum_{i \in \mathcal{B}_{p,lt}} E_{pfi,lt} \mathbb{1}\left(i \in \mathcal{B}_p^{p,kl}\right)}{\sum_{i \in \mathcal{B}_{p,lt}} E_{pfi,lt}}$

- Back

(a) Europe **(b)** United States of America

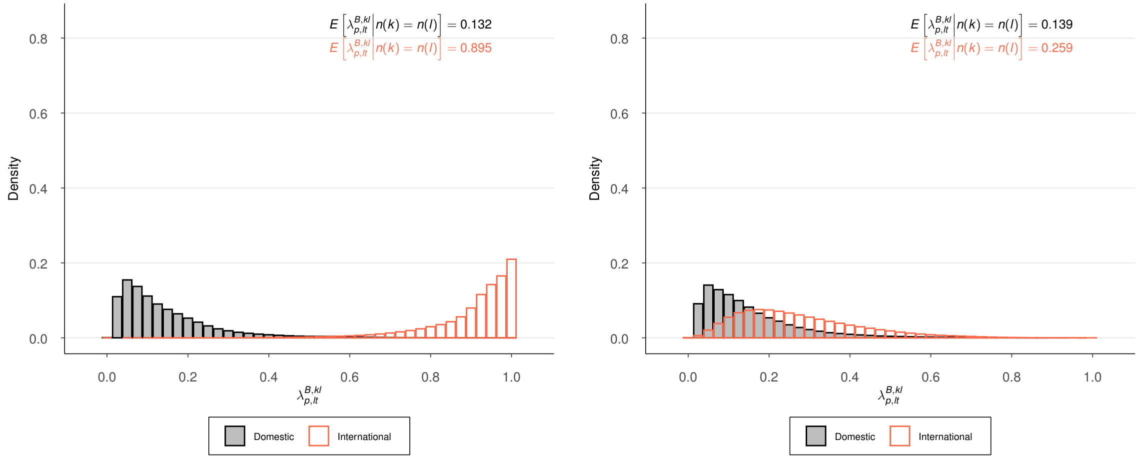


Figure 11: Differences in product availability: Variety-level (Expenditure)

... but so are differences in product availability - $1 - \frac{\sum_{i \in \mathcal{B}_{p,lt}} \mathbb{1}\left(i \in \mathcal{B}_p^{kl}\right)}{\left|\mathcal{B}_{p,lt}\right|}$ -

Back

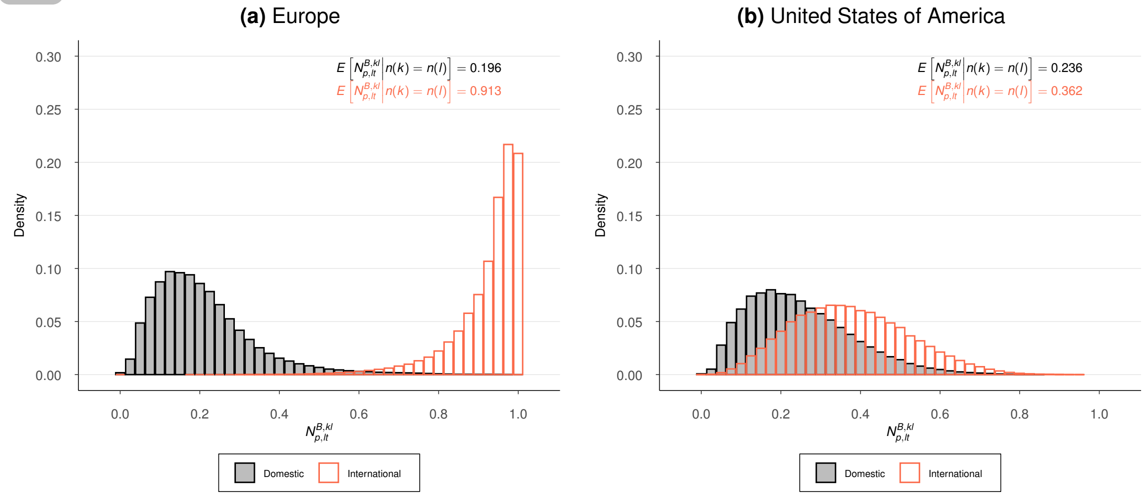


Figure 12: Product availability differences: Variety-level (Numbers) - Branded and Private label

... but so are differences in product availability - $1 - \frac{\sum_{i \in \mathcal{B}_{p,lt}} \mathbb{1}\left(i \in \mathcal{B}_p^{kl}\right)}{|\mathcal{B}_{p,lt}|}$ -

Back

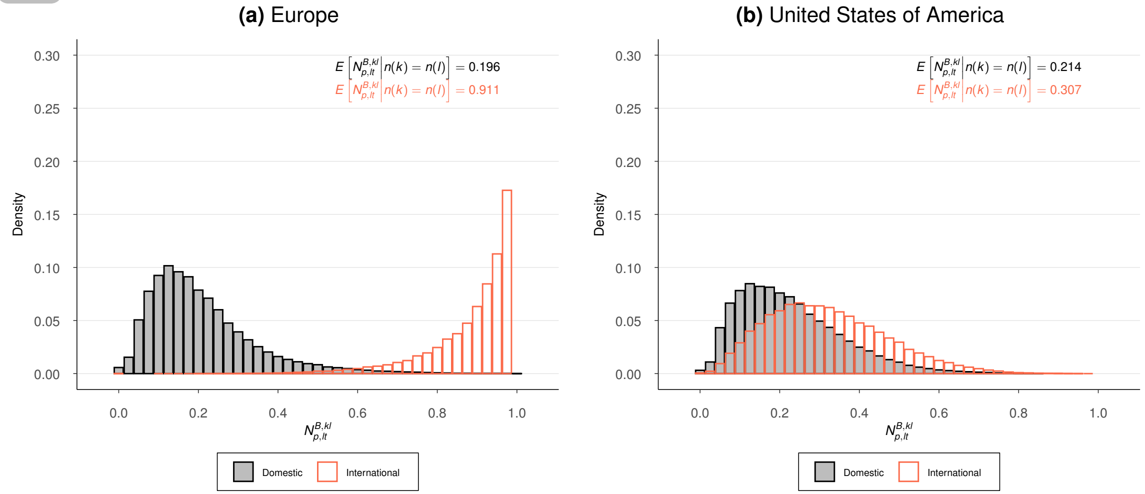


Figure 13: Product availability differences: Variety-level (Numbers) - Branded

... but so are differences in product availability - $1 - \frac{\sum_{f \in \mathcal{F}_{p,lt}} \mathbb{1}\left(f \in \mathcal{F}_p^{kl}\right)}{|\mathcal{F}_{p,lt}|}$ -

Back

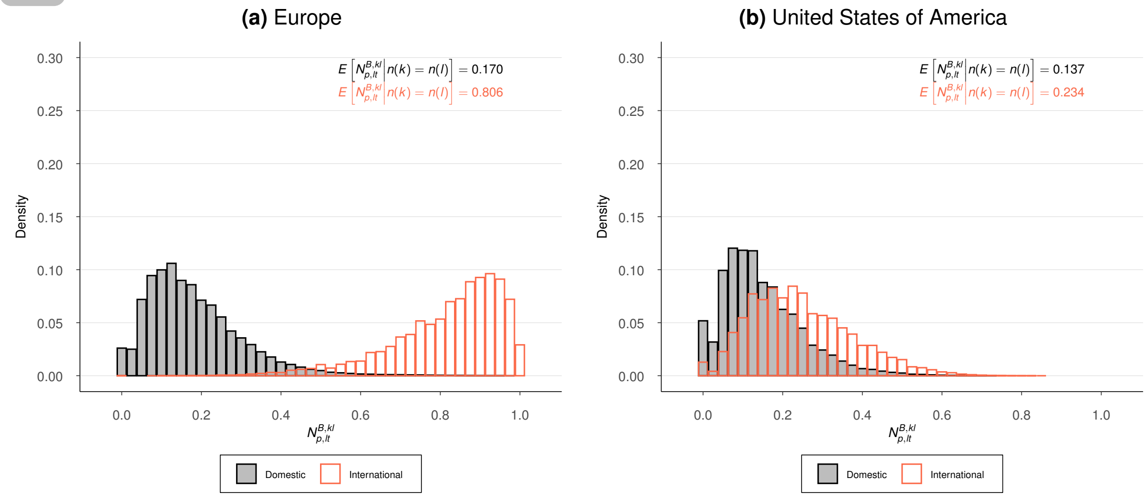


Figure 14: Differences in product availability: Firm-level (Numbers)

... but so are differences in product availability - $1 - \frac{\sum_{f \in \mathcal{F}_{p,lt}} E_{pf,lt} \mathbb{1}\left(f \in \mathcal{F}_p^{kl}\right)}{\sum_{f \in \mathcal{F}_{p,lt}} E_{pf,lt}}$

Back

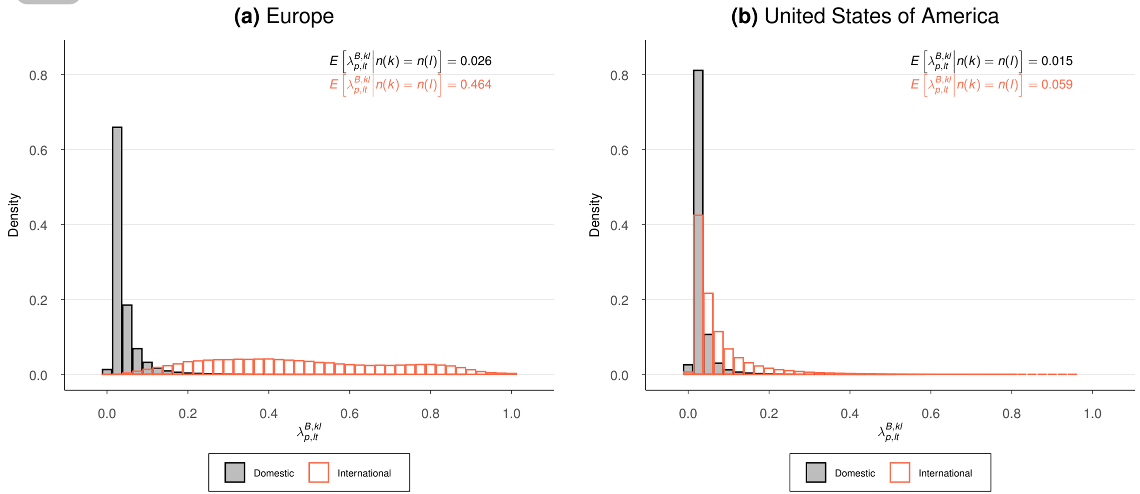


Figure 15: Differences in product availability: Firm-level (Expenditure)

Step 1: Preferences - Back

Consumers in region l at time t have the following preferences:

- **Across product categories**, there is a homothetic and separable aggregator:

$$U(C_{lt}) = F\left(\left\{C_{p,lt}\right\}_{p=1}^{\mathcal{P}}\right)$$

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- **Within product categories**, consumers substitute between **firms** and **varieties** with nested CES preferences

$$C_{p,lt} = \left(\sum_{f \in \Omega_{p,lt}} \left(\xi_{pf,lt} C_{pf,lt}\right)^{\frac{\eta_p - 1}{\eta_p}}\right)^{\frac{\eta_p}{\eta_p - 1}}, \quad C_{pf,lt} = \left(\sum_{i \in \Omega_{pf,lt}} \left(\xi_{pfi,lt} C_{pfi,lt}\right)^{\frac{\sigma_p - 1}{\sigma_p}}\right)^{\frac{\sigma_p}{\sigma_p - 1}}$$

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Utility functions are homogenous of degree 1 in consumer taste, therefore we **normalize** them as follows:

$$\tilde{\xi}_{fp,lt} \equiv \left(\prod_{i\in\Omega_{pf,lt}} \xi_{pfi,lt}\right)^{\frac{1}{N_{pf,lt}}} = \left(\prod_{i\in\Omega_{pf,lt+1}} \xi_{pfi,lt+1}\right)^{\frac{1}{N_{pf,lt+1}}} \equiv \tilde{\xi}_{pf,lt+1}$$

Step 1: Cost-of-living Differences

Back

From Redding & Weinstein (2020), cost-of-living differences between region k and l are the ratio of unit expenditure functions in k and l respectively,

$$\frac{P_{p,kt}}{P_{p,lt}} = \prod_{f \in \Omega_p^{kl}} \left[\left(\frac{P_{pf,kt}}{P_{pf,lt}} \right) \right]^{\frac{1}{N_p^{kl}}} \cdot \prod_{f \in \Omega_p^{kl}} \left[\left(\frac{\xi_{pf,kt}}{\xi_{pf,lt}} \right) \right]^{-\frac{1}{N_p^{kl}}} \cdot \prod_{f \in \Omega_p^{kl}} \left[\left(\frac{S_{pf,kt}^{kl}}{S_{pf,lt}^{kl}} \right)^{\frac{1}{\eta_p - 1}} \right]^{\frac{1}{N_p^{kl}}} \cdot \left(\frac{\lambda_{p,kt}^{kl}}{\lambda_{p,lt}^{kl}} \right)^{\frac{1}{\eta_p - 1}}$$

with $\Omega_{p,lt}$ the set of common firms.

Step 1: Cost-of-living Differences

Back

From Redding & Weinstein (2020), cost-of-living differences between region k and l are the ratio of unit expenditure functions in k and l respectively,

$$\frac{P_{p,kt}}{P_{p,lt}} = \prod_{f \in \Omega_p^{kl}} \left[\left(\frac{P_{pf,kt}}{P_{pf,lt}} \right) \right]^{\frac{1}{N_p^{kl}}} \cdot \prod_{f \in \Omega_p^{kl}} \left[\left(\frac{\xi_{pf,kt}}{\xi_{pf,lt}} \right) \right]^{-\frac{1}{N_p^{kl}}} \cdot \prod_{f \in \Omega_p^{kl}} \left[\left(\frac{S_{pf,kt}^{kl}}{S_{pf,lt}^{kl}} \right)^{\frac{1}{\eta_p - 1}} \right]^{\frac{1}{N_p^{kl}}} \cdot \left(\frac{\lambda_{p,kt}^{kl}}{\lambda_{p,lt}^{kl}} \right)^{\frac{1}{\eta_p - 1}}$$

with $\Omega_{p,lt}$ the set of common firms. **Average Law of One Price (LOP) deviations**:

$$\prod_{f \in \Omega_p^{kl}} \left[\left(\frac{P_{pf,kt}}{P_{pf,lt}} \right) \right]^{\frac{1}{N_p^{kl}}}$$

Step 1: Cost-of-living Differences

Back

From Redding & Weinstein (2020), cost-of-living differences between region k and l are the ratio of unit expenditure functions in k and l respectively,

$$\frac{P_{p,kt}}{P_{p,lt}} = \prod_{f \in \Omega_p^{kl}} \left[\left(\frac{P_{pf,kt}}{P_{pf,lt}} \right) \right]^{\frac{1}{N_p^{kl}}} \cdot \prod_{f \in \Omega_p^{kl}} \left[\left(\frac{\xi_{pf,kt}}{\xi_{pf,lt}} \right) \right]^{-\frac{1}{N_p^{kl}}} \cdot \prod_{f \in \Omega_p^{kl}} \left[\left(\frac{S_{pf,kt}^{kl}}{S_{pf,lt}^{kl}} \right)^{\frac{1}{\eta_p - 1}} \right]^{\frac{1}{N_p^{kl}}} \cdot \left(\frac{\lambda_{p,kt}^{kl}}{\lambda_{p,lt}^{kl}} \right)^{\frac{1}{\eta_p - 1}}$$

with $\Omega_{p,lt}$ the set of common firms. **Unweighted average Taste differences**:

$$\prod_{f \in \Omega_p^{kl}} \left[\left(\frac{\xi_{pf,kt}}{\xi_{pf,lt}} \right) \right]^{-\frac{1}{N_p^{kl}}} = 1$$

Step 1: Cost-of-living Differences

Back

From Redding & Weinstein (2020), cost-of-living differences between region k and l are the ratio of unit expenditure functions in k and l respectively,

$$\frac{P_{p,kt}}{P_{p,lt}} = \prod_{f\in\Omega_p^{kl}}\left[\left(\frac{P_{pf,kt}}{P_{pf,lt}}\right)\right]^{\frac{1}{N_p^{kl}}} \cdot \prod_{f\in\Omega_p^{kl}}\left[\left(\frac{\xi_{pf,kt}}{\xi_{pf,lt}}\right)\right]^{-\frac{1}{N_p^{kl}}} \cdot \prod_{f\in\Omega_p^{kl}}\left[\left(\frac{S_{pf,kt}^{kl}}{S_{pf,lt}^{kl}}\right)^{\frac{1}{\eta_p-1}}\right]^{\frac{1}{N_p^{kl}}} \cdot \left(\frac{\lambda_{p,kt}^{kl}}{\lambda_{p,lt}^{kl}}\right)^{\frac{1}{\eta_p-1}}$$

with $\Omega_{p,lt}$ the set of common firms. **Average expenditure share differences:**

$$\prod_{f\in\Omega_p^{kl}}\left[\left(\frac{S_{pf,kt}^{kl}}{S_{pf,lt}^{kl}}\right)^{\frac{1}{\eta_p-1}}\right]^{\frac{1}{N_p^{kl}}}, \qquad \text{where} \quad S_{pf,lt}^{kl} \equiv \frac{P_{pf,lt}C_{pf,lt}}{\sum_{f\in\Omega_p^{kl}} P_{pf,lt}C_{pf,lt}} \forall f \in \Omega_p^{kl}$$

Through η_p this term captures

- Substitution effects when $P_{pf,kt} \neq P_{pf,lt}$ and $\xi_{pf,kt} = \xi_{pf,lt}$
- Taste differences when $P_{pf,kt} = P_{pf,kt}$ and $\xi_{pf,kt} \neq \xi_{pf,lt}$

Step 1: Cost-of-living Differences

Back

From Redding & Weinstein (2020), cost-of-living differences between region k and l are the ratio of unit expenditure functions in k and l respectively,

$$\frac{P_{p,kt}}{P_{p,lt}} = \prod_{f\in\Omega_p^{kl}} \left[\left(\frac{P_{pf,kt}}{P_{pf,lt}}\right)\right]^{\frac{1}{N_p^{kl}}} \cdot \prod_{f\in\Omega_p^{kl}} \left[\left(\frac{\xi_{pf,kt}}{\xi_{pf,lt}}\right)\right]^{-\frac{1}{N_p^{kl}}} \cdot \prod_{f\in\Omega_p^{kl}} \left[\left(\frac{S^{kl}_{pf,kt}}{S^{kl}_{pf,lt}}\right)^{\frac{1}{\eta_p - 1}}\right]^{\frac{1}{N_p^{kl}}} \cdot \left(\frac{\lambda^{kl}_{p,kt}}{\lambda^{kl}_{p,lt}}\right)^{\frac{1}{\eta_p - 1}}$$

with $\Omega_{p,lt}$ the set of common firms. **Choice set differences:**

$$\left(\frac{\lambda^{kl}_{p,kt}}{\lambda^{kl}_{p,lt}}\right)^{\frac{1}{\eta_p - 1}}, \qquad \text{where} \quad \lambda^{kl}_{pf,lt} \equiv \frac{\sum_{f\in\Omega_p^{kl}} P_{pf,lt} C_{pf,lt}}{\sum_{f\in\Omega_{p,lt}} P_{pf,lt} C_{pf,lt}}$$

Step 2: Technology and Market structure

Back

- We consider a **CRS production technology** and **one production location** in $z \in \mathcal{L}$:

$$\mathrm{TC}_{pf,t} = \underbrace{\sum_{l \in \mathcal{L}} \sum_{i \in \Omega_{pf,lt}} \phi_{pfi,zt} \cdot Q_{pfi,lt}}_{\text{Variable costs}} + \underbrace{F_{pf,t} \cdot \mathbb{1}\left(\sum_{l \in \mathcal{L}} \sum_{i \in \Omega_{pf,lt}} Q_{pfi,lt} > 0\right)}_{\text{Fixed production costs}}$$

- Market structure consists of **iceberg trade costs** with **monopolistic competition** (for now):

$$P_{pfi,lt} = \mu_{pfi,lt} \mathrm{MC}_{pfi,lt}, \qquad \text{where} \quad \mu_{pfi,lt} = \frac{\eta_{p(i)}}{\eta_{p(i)} - 1}, \quad \mathrm{MC}_{pfi,lt} = \phi_{pfi,zt} \cdot t_{pfi,t}(\boldsymbol{X}^{zl}) \cdot \left(1 + \tau_{pfi,t} B^{zl}\right)$$

- Firms **choose the set of barcodes** to offer in each country:

$$\max_{\Omega_{pf,lt}} = \underbrace{\sum_{l \in n} \sum_{i \in \Omega_{pf,lt}} \left(P_{pfi,lt} - \mathrm{MC}_{pfi,lt}\right) Q_{pfi,lt}}_{\text{Variable profits}} - \underbrace{F^X_{pf,t} \cdot \mathbb{1}\left(\sum_{l \in n} \sum_{i \in \Omega_{pf,lt}} B^{zl} Q_{pfi,lt} > 0\right)}_{\text{Market entry cost}} - \underbrace{\sum_{i \in \Omega_{pf,lt}} F^X_{pfi,t} \cdot \mathbb{1}\left(\sum_{l \in n} B^{zl} Q_{pfi,lt} > 0\right)}_{\text{Per variety fixed cost}}$$

Estimating σ_p - Strategy

Take logs of the residual product variety level demand curve:

$$c_{pfi,lt} = -\sigma_p p_{pfi,lt} + \sigma_p p_{pf,lt} + c_{pf,lt} + (\sigma_p - 1)\ln\left(\xi_{pfi,lt}\right)$$

Consider this expression at the retail chain level:

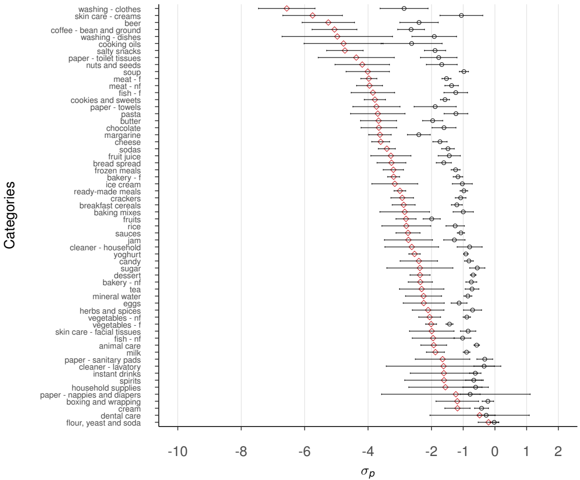
$$c_{pfic,lt} = -\sigma_p p_{pfic,lt} + \theta_{pfic,n(l)y(t)} + \theta_{pfic,n(l)w(t)} + \lambda_{pfc,lt} + \varepsilon_{pfic,lt}$$

- $\lambda_{pfc,lt}$: Condition on price and quantity index and any other firm-chain-region specific demand shock
- $\theta_{pfic,n(l)y(t)}$ and $\theta_{pfic,n(l)w(t)}$ take out seasonal promotional activity.
- We use a Hausman (1996)-instrument to guard against residual regional demand shock:

$$\bar{p}_{pfic,-lt} \equiv \frac{1}{\mathcal{L}_n} \sum_{k \in n \setminus l} p_{pfic,kt}$$

Estimating σ_p - Results: $\hat{\mathbb{E}}[\hat{\sigma_p}] = -2.77$ with $10\% - 90\% : [-4.77, -1.15]$

Figure 16: Elasticity of substitution σ_p



Estimating η_p - Strategy

Take logs of the residual product variety level demand curve:

$$c_{pf,lt} = -\sigma_p p_{pf,lt} + \sigma_p p_{p,lt} + c_{p,lt} + (\sigma_p - 1)\ln\left(\xi_{pf,lt}\right)$$

Consider this expression at the retail chain level:

$$c_{pf,lt} = -\sigma_p p_{pf,lt} + \theta_{pf,n(l)y(t)} + \theta_{pf,n(l)w(t)} + \lambda_{p,lt} + \varepsilon_{pf,lt}$$

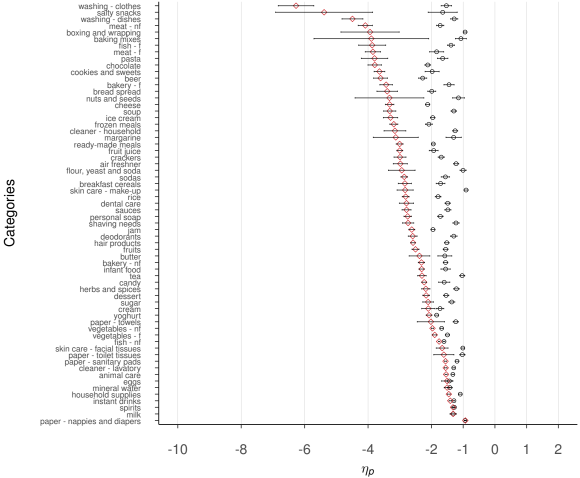
- $\lambda_{p,lt}$: Condition on price and quantity index and any other region-specific demand shock:
- $\theta_{pf,n(l)(y(t))}$ and $\theta_{pf,n(l)(w(t))}$ take out seasonal promotional activity.
- We use a structural-instrument to guard against residual regional demand shock:

$$P_{pf,lt} = \tilde{P}_{pf,lt} \underbrace{\left(\sum_{i \in \mathcal{B}_{fp,lt}} \frac{S_{fpi,lt}}{\left(\prod_{i \in \mathcal{B}_{fp,lt}} S_{fpi,lt}\right)^{\frac{1}{N_{fp,lt}}}} \right)^{\frac{1}{1-\sigma_p}}}_{\text{instrument}} \left(\prod_{i \in \mathcal{B}_{fp,lt}} \xi_{fpi,lt} \right)^{-\frac{1}{N_{fp,lt}}}, \quad \text{with} \quad \left(\prod_{i \in \mathcal{B}_{fp,lt}} \xi_{fpi,lt} \right)^{\frac{1}{N_{fp,lt}}} = \left(\prod_{i \in \mathcal{B}_{fp,lt-1}} \xi_{fpi,lt-1} \right)^{\frac{1}{N_{fp,lt-1}}}$$

Expenditure

Estimating η_p - Results: $\hat{\mathbb{E}}[\hat{\eta_p}] = -3.10$ with $10\% - 90\% : [-4.84, -1.71]$

Figure 17: Elasticity of substitution η_p



Decomposing cost-of-living differences - Back

Table 5: Regional cost-of-living differences - Summary statistics

	Quantiles of $P^{kl}_{p,t}$			Variance decomposition of $P^{kl}_{p,t}$		
$P^{kl}_{p,t}$	Q_{10}	Q_{50}	Q_{90}	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
EUROPE						
$\mathbb{1}\left(B^{kl}=0\right)$	$-.365$	$-.003$	$.441$	$.864$	$.002$	$.134$
	$[-.385, -.351]$	$[-.004, -.002]$	$[.424, .466]$	$[.845, .88]$	$[.002, .002]$	$[.118, .153]$
$\mathbb{1}\left(B^{kl}=1\right)$	-1.12	$-.071$	1.006	$.579$	$.021$	$.4$
	$[-1.18, -1.078]$	$[-.076, -.065]$	$[.959, 1.07]$	$[.496, .629]$	$[.016, .025]$	$[.351, .486]$
USA						
$\mathbb{1}\left(B^{kl}=0\right)$	$-.346$	$.14$	$.79$	$.852$	0	$.148$
	$[-.36, -.333]$	$[.135, .146]$	$[.741, .853]$	$[.79, .879]$	$[0, 0]$	$[.121, .21]$
$\mathbb{1}\left(B^{kl}=1\right)$	$-.638$	$.02$	$.728$	$.826$	$-.001$	$.175$
	$[-.675, -.609]$	$[.019, .021]$	$[.693, .773]$	$[.781, .843]$	$[-.002, 0]$	$[.158, .22]$

Detecting cross-border market segmentation - Back

Table 6: Geographic market segmentation: Estimation results ($\varepsilon = 0.05$)

Y	$P^{kl}_{p,t}$ (1)	$T^{kl}_{p,t}$ (2)	$L^{kl}_{p,t}$ (3)	$\Lambda^{kl}_{p,t}$ (4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.369***	.3009***	.1009***	.2685***
	[.3443, .3979]	[.2799, .3238]	[.0991, .1028]	[.2502, .2924]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2476	.226	.0125	.043
Nr. treated	68	68	68	68
Nr. matched units	1	1	1	1
Nr. unique controls	41	41	41	41
Nr. obs	4,624	4,624	4,624	4,624
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0103***	.0095***	.0058***	.0164***
	[.0037, .0153]	[.0032, .0152]	[.0054, .0063]	[.0145, .018]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.3987	.3438	.0236	.0871
Nr. treated	256	256	256	256
Nr. matched units	1	1	1	1
Nr. unique controls	63	63	63	63
Nr. obs	17,084	17,084	17,084	17,084

Notes: Block-bootstrapped standard errors on 50 iterations at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Detecting cross-border market segmentation - Back

Table 7: Geographic market segmentation: Estimation results ($\varepsilon = 0.10$)

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	$.395^{***}$	$.3186^{***}$	$.0968^{***}$	$.3006^{***}$
	[.3696, .4338]	[.3016, .3439]	[.0958, .0976]	[.2803, .329]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2466	.2265	.0125	.0402
Nr. treated	154	154	154	154
Nr. matched units	3	3	3	3
Nr. unique controls	116	116	116	116
Nr. obs	26,192	26,192	26,192	26,192
USA				
$\hat{\gamma}_{Y,\varepsilon}$	$.0177^{***}$	$.0173^{***}$	$.0062^{***}$	$.0187^{***}$
	[.0141, .0201]	[.0144, .0201]	[.0059, .0065]	[.0172, .0208]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4067	.3494	.0242	.0902
Nr. treated	623	623	623	623
Nr. matched units	3	3	3	3
Nr. unique controls	116	116	116	116
Nr. obs	99,464	99,464	99,464	99,464

Notes: Block-bootstrapped standard errors on 50 iterations at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Detecting cross-border market segmentation - Back

Table 8: Geographic market segmentation: Estimation results ($\varepsilon = 0.10$) - Markups

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$MC^{kl}_{p,t}$	$\mathcal{M}^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)	(5)
EUROPE					
$\hat{\gamma}_{Y,\varepsilon}$	.3787***	.3041***	.0917***	.0113***	.2972***
	[.3548, .4114]	[.2866, .3276]	[.0904, .0928]	[.0104, .0121]	[.2768, .3259]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.26	.2372	.021	.0143	.0427
Nr. treated	146	146	146	146	146
Nr. matched units	1	1	1	1	1
Nr. unique controls	81	81	81	81	81
Nr. obs	9,928	9,928	9,928	9,928	9,928
USA					
$\hat{\gamma}_{Y,\varepsilon}$	.0049*	.0092***	.0059***	.0024***	.0145***
	[−.0008, .0098]	[.005, .0138]	[.0054, .0063]	[.0019, .0028]	[.0127, .0165]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4168	.356	.038	.0245	.0926
Nr. treated	0	0	0	0	0
Nr. matched units	1	1	1	1	1
Nr. unique controls	0	0	0	0	0
Nr. obs	40,100	40,100	40,100	40,100	40,100

Notes: Block-bootstrapped standard errors on 50 iterations at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Detecting cross-border market segmentation - Back

Table 9: Geographic market segmentation: Estimation results ($\varepsilon = 0.10$) - CES preferences

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.3462***	.2556***	.1395***	.4264***
	[.3142, .3945]	[.2269, .2939]	[.1383, .1412]	[.3849, .4874]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.1425	.1218	.0131	.0352
Nr. treated	154	154	154	154
Nr. matched units	3	3	3	3
Nr. unique controls	116	116	116	116
Nr. obs	26,192	26,192	26,192	26,192
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0069***	.0027**	.0069***	.0195***
	[.004, .0099]	[.0008, .0047]	[.0065, .0071]	[.0159, .0248]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2661	.2136	.0255	.0808
Nr. treated	623	623	623	623
Nr. matched units	3	3	3	3
Nr. unique controls	116	116	116	116
Nr. obs	99,467	99,467	99,467	99,467

Notes: Block-bootstrapped standard errors on 50 iterations at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Detecting cross-border market segmentation - ▸ Back

Table 10: Robustness: Elasticities - Cutoff: 10% and Nr. controls: 1 - Europe

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
$\hat{\eta}+0, \hat{\sigma}+0$				
$\hat{\gamma}_{Y,\varepsilon}$	.3787***	.3041***	.0967***	.2972***
	[.3548, .4114]	[.2866, .3276]	[.0953, .0977]	[.2768, .3259]
$\hat{\eta}+0, \hat{\sigma}+1$				
$\hat{\gamma}_{Y,\varepsilon}$	.3259***	.2684***	.0967***	.2514***
	[.3168, .3403]	[.2595, .2794]	[.0953, .0977]	[.2432, .2615]
$\hat{\eta}+0, \hat{\sigma}+2$				
$\hat{\gamma}_{Y,\varepsilon}$	.3181***	.2628***	.0967***	.2423***
	[.3097, .3314]	[.2538, .274]	[.0953, .0977]	[.2346, .2538]
$\hat{\eta}+0, \hat{\sigma}+3$				
$\hat{\gamma}_{Y,\varepsilon}$	.3158***	.2611***	.0967***	.239***
	[.3077, .3284]	[.252, .2725]	[.0953, .0977]	[.2312, .2506]
$\hat{\eta}+1, \hat{\sigma}+0$				
$\hat{\gamma}_{Y,\varepsilon}$	.3213***	.2337***	.0967***	.2126***
	[.2954, .358]	[.2168, .2553]	[.0953, .0977]	[.1938, .2438]
$\hat{\eta}+1, \hat{\sigma}+1$				
$\hat{\gamma}_{Y,\varepsilon}$	.2323***	.176***	.0967***	.1496***
	[.2268, .2388]	[.1715, .1812]	[.0953, .0977]	[.1462, .1549]
$\hat{\eta}+1, \hat{\sigma}+2$				
$\hat{\gamma}_{Y,\varepsilon}$	.2111***	.1634***	.0967***	.1337***
	[.2077, .2149]	[.1597, .1663]	[.0953, .0977]	[.1312, .1361]
$\hat{\eta}+1, \hat{\sigma}+3$				
$\hat{\gamma}_{Y,\varepsilon}$	.2023***	.1586***	.0967***	.1268***
	[.1993, .2059]	[.1552, .1615]	[.0953, .0977]	[.1246, .129]

Notes: Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Detecting cross-border market segmentation - ▸ Back

Table 11: Robustness: Elasticities - Cutoff: 10% and Nr. controls: 1 - USA

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
$\hat{\eta}+0, \hat{\sigma}+0$				
$\hat{\gamma}_{Y,\varepsilon}$	$.0049^{*}$	$.0092^{***}$	$.0062^{***}$	$.0145^{***}$
	$[-.0008, .0098]$	$[.005, .0138]$	$[.0059, .0065]$	$[.0127, .0165]$
$\hat{\eta}+0, \hat{\sigma}+1$				
$\hat{\gamma}_{Y,\varepsilon}$	$.0141^{***}$	$.0151^{***}$	$.0062^{***}$	$.0166^{***}$
	$[.0109, .0167]$	$[.0115, .0182]$	$[.0059, .0065]$	$[.015, .0184]$
$\hat{\eta}+0, \hat{\sigma}+2$				
$\hat{\gamma}_{Y,\varepsilon}$	$.0174^{***}$	$.0173^{***}$	$.0062^{***}$	$.0177^{***}$
	$[.0144, .0204]$	$[.014, .0201]$	$[.0059, .0065]$	$[.0161, .0194]$
$\hat{\eta}+0, \hat{\sigma}+3$				
$\hat{\gamma}_{Y,\varepsilon}$	$.0193^{***}$	$.0185^{***}$	$.0062^{***}$	$.0183^{***}$
	$[.0163, .0222]$	$[.0155, .0215]$	$[.0059, .0065]$	$[.0168, .0201]$
$\hat{\eta}+1, \hat{\sigma}+0$				
$\hat{\gamma}_{Y,\varepsilon}$	$-.0074^{***}$	$-.0028^{*}$	$.0062^{***}$	$.0046^{***}$
	$[-.0118, -.004]$	$[-.0062, .0004]$	$[.0059, .0065]$	$[.0034, .0056]$
$\hat{\eta}+1, \hat{\sigma}+1$				
$\hat{\gamma}_{Y,\varepsilon}$	$.0005$	$.002^{***}$	$.0062^{***}$	$.0054^{***}$
	$[-.0011, .0025]$	$[.0001, .0037]$	$[.0059, .0065]$	$[.005, .0058]$
$\hat{\eta}+1, \hat{\sigma}+2$				
$\hat{\gamma}_{Y,\varepsilon}$	$.0038^{***}$	$.004^{***}$	$.0062^{***}$	$.006^{***}$
	$[.0024, .0054]$	$[.0023, .0052]$	$[.0059, .0065]$	$[.0057, .0064]$
$\hat{\eta}+1, \hat{\sigma}+3$				
$\hat{\gamma}_{Y,\varepsilon}$	$.0057^{***}$	$.0052^{***}$	$.0062^{***}$	$.0065^{***}$
	$[.0043, .007]$	$[.0037, .0063]$	$[.0059, .0065]$	$[.0061, .0069]$

Notes: Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

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