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We develop a new approach to measure the sources of geographic goods market segmentation. Our cost-of-living approach uncovers the relative importance of price and product availability differences, while accounting for taste differences. We implement our methodology on regionally disaggregated consumer goods data in the EU and US. The analysis reveals that price, and especially, product availability differences are much larger between than within European countries, and are only marginally larger between than within US states. Our findings imply that US states are geographically integrated, whereas EU countries remain segmented, due to trade frictions that mainly relate to fixed costs.

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1 Introduction

Increases in geographic market integration have historically occurred through reductions in transport costs (e.g. Pascali (2017) and decreased cross-border trade frictions (e.g. Bernhofen & Brown (2005)). There is also mounting evidence that increased integration of individual spatial units into larger interconnected markets increases aggregate welfare (e.g. Donaldson & Hornbeck (2016) and Fajgelbaum & Redding (2022)). Assessing the presence and the sources of cross-border geographic market segmentation at a given point in time remains, therefore, a question of central importance.

Two strategies have emerged to evaluate whether markets are geographically integrated or segmented. One strategy assesses whether prices of identical products differ significantly more between than within countries (e.g. Engel & Rogers (1996) and Goldberg & Knetter (1997)). Although price differences, or Law of One Price (LOP) deviations, potentially imply the presence of trade frictions that relate to variable costs, this strategy ignores differences in product availability. Therefore, it cannot speak to the presence of trade frictions related to fixed costs of market entry. An alternative strategy evaluates whether trade shares discontinuously fall at borders (e.g. McCallum (1995)). Differences in trade shares may indeed capture both differences in prices and product availability, and thereby reflect both variable and fixed trade frictions. However, differences in trade shares may also stem from cross-country differences in consumer taste.

In this paper, we develop an integrated framework to assess the presence of cross-border geographic market segmentation and uncover its sources by measuring the importance of both price and product availability differences as manifestations of cross-border market segmentation. To overcome the above-mentioned concerns, we rely on a new dataset and propose a two-step approach: we first measure price and product availability differences separately from consumer taste and then derive testable conditions that compare these differences between and within countries. We show that these conditions are sufficient to detect the presence of cross-border variable and fixed trade frictions, and thus cross-border market segmentation, in a large class of international trade models.

The dataset comprises 68 tradeable final good categories and is constructed from detailed household-level and product-level scanner datasets, covering four EU countries and all US states. It is ideally suited for three reasons. First, the data is based on household-level scanner data which provides a comprehensive picture of prices paid and product availability. In contrast, scraped or customs datasets typically only cover varieties available online or that passed through customs. Second, in addition to observing consumers' purchasing behavior, we also observe detailed household characteristics such as the location of residence. This enables us to spatially disaggregate the dataset and exploit within- and between-country variation in both prices and product availability. Finally, the dataset covers both EU countries and US states. Like Head & Mayer (2021), we leverage this aspect to assess whether and to which extent cross-border market integration is (still) weaker in the EU than in the US.

A first look at the data reveals that there are considerable price and product availability differences across European regions, while such differences are marginal within the same country. More specifically, absolute price differences are on average 19% between regions belonging to different countries, and the share of common varieties in two regions belonging to different countries is usually below 25%. In stark contrast, price and product availability differences between US states are small and very comparable to the differences within US states. Although these findings are suggestive of cross-border market segmentation, they do not reveal the relative importance of price and product availability differences and how they relate to cross-border variable and fixed trade frictions.

To this end, we propose a two-step approach. In the first step, we leverage the fact that cost-of-living differences between regions can be decomposed into differences in prices, product availability, and remaining differences in consumer taste. In the second step, we develop a spatial differencing approach that isolates variation in prices and product availability due to cross-border market segmentation between EU countries or US states from variation stemming from natural (unobserved) transport costs that also occur within countries or states. We now elaborate in more detail on both steps.

In the first step, we build a theoretical model of consumer behavior and derive an expression for regional cost-of-living differences. We model preferences as a nested CES demand system, with one nest at the firm level and one at the variety level. We use the CES framework as it is the workhorse framework to understand the gains from market integration and to conduct policy counterfactuals (e.g. Arkolakis et al. (2012) and Allen et al. (2020)). Given a normalization of the region-specific geometric average consumer taste level, regional cost-of-living differences can be conveniently decomposed into three terms: (1) expenditure-weighted average LOP deviations, (2) differences in product availability, and (3) pure taste differences (see Redding & Weinstein (2020) for an analogous decomposition of cost-of-living changes over time). This enables us to measure the two manifestations of cross-border market segmentation in a common unit. At the same time, they are empirically separated from regional differences in consumer taste. Estimating the elasticities of substitution and regional cost-of-living differences reveals the importance of accounting for pure taste differences. Furthermore, product availability differences are quantitatively more important than price differences as a source of regional cost-of-living differences, both in the EU and US.

In the second step, we consider a spatial differencing strategy that delivers testable conditions to detect cross-border market segmentation. In the spirit of the trade flows analysis of Santamaria et al. (2020), we compare price and product availability differences between regions belonging to different countries with those between regions of the same country. By focusing on geographically close region pairs, we filter out price and product availability differences that would be present regardless of cross-border market segmentation, for instance, due to unobserved transport costs. Moreover, we show that under commonly made additional restrictions on the market environment and technology, e.g. (nested) CES-preferences and constant marginal costs, this strategy is sufficient to detect the presence of variable and fixed trade frictions, and thus both sources of cross-border geographic market segmentation.

Implementing our spatial differencing strategy yields three main results. First, cost-of-living differences are roughly 2.5 times larger between than within EU countries. In contrast, cost-of-living differences are only marginally larger between US states compared to within US states. Our structural decomposition shows that taste differences account for a little over 80% of the variation in cost-of-living differences within EU countries and across US states. This illustrates that it is quantitatively important to control for taste differences when assessing the presence of cross-border market segmentation.

Second, both price and product availability differences are significantly higher and economically much more important between than within EU countries. While price and product availability differences are also significantly higher between than within US states, the differences are quantitatively small.[1] This point is further corroborated by comparing the observed distribution with a distribution of placebo estimates. While the differences between versus within EU countries are unlikely to be drawn from the distribution of placebo estimates, the estimated average effect between versus within US states is firmly within the 5^{th} and 95^{th} percentiles of the distribution of placebo estimates. Under the additional restrictions on the market environment and technology, our testable conditions imply that trade frictions still geographically segment the final goods markets of European countries, but not of US states. In other words, while we require both variable and fixed trade frictions to explain the price and product availability differences between EU countries, no cross-border frictions are required to fit the US data. Our findings on the EU trade frictions are particularly noteworthy, since we focus our European analysis on a subset of EU countries that are arguably more integrated.

Third, product availability differences between European countries quantitatively dominate price differences. In particular, price differences are around 10 percentage points larger between than within EU countries. In contrast, differences in product availability are around 30% larger between EU than within countries. Hence, in terms of cost-of-living differences, this suggests that cross-border segmentation through fixed trade frictions is three times more important than segmentation stemming from variable trade frictions, even though the latter has received the most attention in the literature.

Related literature and outline We contribute to three strands of literature. Methodologically, our paper relates to an extensive literature on measuring cost-of-living differences that relies on the family of CES preference systems. Building on the work of Sato (1976) and Vartia (1976), cost-of-living indices now account for changes in variety (e.g. Feenstra (1994) and Broda & Weinstein (2006)) and for changes in consumer tastes (Redding & Weinstein (2020)). However, the predominant focus has been on cost-of-living changes over time, and comparatively little is known about the sources of spatial differences between regions. Using more restrictive setups, Handbury & Weinstein (2015) and Feenstra et al. (2020) estimate within-country cost-of-living differences and Argente et al. (2021) and Cavallo et al. (2022) quantify cost-of-living differences between countries. Importantly, there is no prior work that combines within- and between-country variation in prices and product availability. As

[1]These findings for the USA are also in line with those of Broda & Weinstein (2008) on the US versus Canada. Focusing on LOP deviations and abstracting from product availability differences, they find that the distance-equivalent border effect between both countries is limited.

emphasized in Anderson & Wincoop (2004), combining such variation is crucial to separate cross-border market segmentation from within-country frictions, such as transport costs. Based on our rich framework, we find that differences in consumer tastes are key contributors to within- and between-country variation in cost-of-living differences across both EU and US regions, and that differences in product availability are quantitatively the most important manifestation of cross-border market segmentation across European countries.

Second, we complement the literature that links international price differences to cross-country trade costs. Early studies relying on price index data found immense LOP deviations (e.g. Engel & Rogers (1996) and Crucini et al. (2005)). While this was partly due to aggregation biases (see Broda & Weinstein (2008) and Gorodnichenko & Tesar (2009)), variety-level price data re-affirmed the presence of considerable (albeit smaller) price differences between countries (e.g. Goldberg & Verboven (2001), Gopinath et al. (2011), Cavallo et al. (2014), Fontaine et al. (2020) and Beck et al. (2020)). As the set of products for which between-country price differences can be computed is typically small, the literature lacks a unifying framework that accounts for both price and product availability differences as manifestations of cross-border market segmentation. We develop such a unified framework and show that differences in product availability are quantitatively much more important than price differences as a manifestation of cross-border market segmentation in the EU.

Finally, we contribute to a large literature that aims to measure cross-border market segmentation by estimating whether borders have predictive power for trade shares. In a seminal contribution, McCallum (1995) established that the US-Canada border led to substantially larger reductions in goods trade than regional borders. More sophisticated methods to deal with aggregation and selection biases were subsequently developed, e.g. Anderson & Wincoop (2003), Helpman et al. (2008) and Santamaria et al. (2020). In related work, Head & Mayer (2021) combine regional trade data for the EU and the US to compare the evolution of trade barriers in the US and the EU. However, mapping differences in trade shares into cross-border market segmentation remains difficult when cross-country differences in consumer tastes are substantial. Our framework empirically separates differences in consumer taste from LOP deviations and differences in product availability and shows that it is quantitatively important to do so.

Section 2 provides more detail on the data, and section 3 provides motivating evidence for moving beyond price differences when studying geographic market segmentation. Section 4 introduces our structural framework to compute and decompose regional cost-of-living differences into taste, price and product availability differences. It also develops our spatial differencing strategy to detect geographic market segmentation when transport routes are unobserved. Section 5 provides the estimates of the elasticities of substitution. Finally, section 6 assesses the presence of geographic market segmentation across EU countries and US states, and section 7 concludes.

2 Data

We rely on household-level scanner data comprising 68 tradeable fast-moving consumer goods (FMCG) categories from Belgium, France, Germany, the Netherlands and the US. In each country, a market research firm provides a panel of households with a scanning device to register the number of units bought, the total volume purchased, and the total tax-inclusive monetary value of the transaction for each purchased barcode.[2] In addition, buyers report the retail chain in which the product was purchased. We focus on a relatively stable period from 2010 until 2019, omitting the trough of the financial crisis and the start of the COVID-19 pandemic. We now provide more detail on the construction of the sample, and the dimensions and suitability of the data.

Countries (and states) Among the European countries, we restrict attention to Belgium, France, Germany and the Netherlands for two reasons. First, these countries are probably among the most integrated ones within the European Single Market. All countries were founding partners of the European Economic Area, and they have always partaken in the successive integration efforts to form the European Single Market. As other countries have joined at later stages, our results likely provide a conservative estimate of the degree of market segmentation within the European Single Market. Second, focusing on countries with a common currency makes relying on cost-of-living differences, or real exchange rate variation, more appealing to assess the degree of cross-border market segmentation. When countries use different currencies, variation in nominal exchange rates can spill into real exchange rates when nominal prices are sticky. By focusing on a set of countries that share the same currency, we ensure that real exchange rate variation is mostly determined by real factors and not by financial or monetary shocks (see Heathcote & Perri (2014) and Berka et al. (2018)).

Throughout the paper, we compare differences between EU countries with differences between US states. European policymakers often consider the US as a model of federalism, so the degree of integration between US states serves as a suitable benchmark to evaluate cross-border market integration between EU countries. For consistency, we will use the terms countries and states interchangeably in the rest of the paper.

Regions To understand the degree of cross-border integration (or segmentation), we compare between- and within-country variation in prices and product availability. To this end, we further disaggregate EU countries by defining regions at the NUTS-2 (rev. 2013) level.[3] This yields 83 regions across four EU countries and an average number of sampled households per region-year

[2]The market research firm is GfK in Belgium, Germany, and the Netherlands, and Kantar in France, and we were granted access to these data by AiMark (Advanced International Marketing Knowledge). In the US, the data comes from NielsenIQ and is accessed through the Kilts Center of the Booth School of Business at the University of Chicago.

[3]The NUTS classification is a European standard used for referencing administrative levels within countries. After administrative reforms in 2016, France changed their NUTS classifications. Because the regional variable in the French dataset corresponds to the NUTS2-level of the NUTS-2 (rev. 2013) version, we use the 2013 version of the NUTS regions throughout the paper.

between 527 and 1,784 depending on the country (see Table A.7). Similarly, we further disaggregate US states by defining regions at the Designated Market Area (DMA) level. DMAs are geographic regions that receive similar radio, television and broadcast channels. As they are exposed to very similar advertising efforts, they serve as natural markets within US states. To ensure a minimum number of sampled households, we restrict the set of US states to 43. This yields 124 regions and an average of 755 households per region-year (see again Table A.7).

Households We link household characteristics to each purchase through a unique household identifier reported in the transaction data. Crucially, we observe the household's region of residence and the ZIP code. This allows us to determine variety-level prices, quantities, and product availability at the regional level. To minimize measurement error through occasional consumption or consumers that rotate in and out of the sample in the middle of the year, we include consumers in a given year only if they register transactions in each quarter of the year. Depending on the European country, the main sample includes on average between 3,200 and 23,348 households in each year, which accounts for 60%-91% of total recorded expenditure within the selected categories (see Table A.7). In the USA, the sample comprises of 53,555 households per year on average. Figures A.3 - A.5 illustrate that the resulting distributions of weekly shopping trips, the number of weekly purchases, and the number of purchased barcodes are very similar across European countries. This supports the idea that the consumption baskets are representative, reflect very similar overall purchase behavior across European countries and therefore can be leveraged to compare between and within country variation.[4]

Categories We focus on a set of 68 FMCG categories, ranging from food, alcoholic and non-alcoholic beverages to personal care items that jointly represent around 15% in total final consumer spending. In all countries, the raw data go beyond the 68 categories we include in the final dataset, but we limit the set of categories for two reasons (see Table A.1). First, we only keep categories that are consumed by more than 5% of the households in all countries. Second, we omit categories such as medicines and first aid products because the extent to which consumers can access them through retail stores differs across countries.[5] Still, the final dataset covers most of the recorded expenditure as the included categories always account for a little under 90% of total expenditures in all countries (Table A.2). Figure A.1 shows the distribution of expenditure shares across the included categories.

Varieties The transaction data records purchases at the barcode level, which corresponds to an 8- or 13-digit EAN code in Europe and a UPC in the US. We refer to barcodes as distinct varieties within a category. One example of a variety is a 6-pack 330ML Can Coca-Cola Regular.[6] We

[4] To ensure that we measure product availability in a region as completely as possible, we use the full sample of households when determining the set of available varieties and firms.

[5] For instance, the distribution of these products is much more regulated in Belgium than in the Netherlands.

[6] Generally, barcodes carry a 13-digit identifier. However, there is a small set of varieties that are sold in small packages, e.g. spices or small shampoo bottles, or that are individually sold, e.g. small soda bottles. These varieties have

combine package information obtained from the barcode descriptions with information about units sold, volume sold and expenditure to compute quantity consumed and prices per liter, kilogram or unit.[7] We compute variety-level prices as the ratio of expenditure and quantity sold.

Scanner data offer three distinct advantages to study the degree of geographic market segmentation. First, observing variety-level prices ensures that LOP deviations do not stem from differences in unobserved product characteristics. Since barcodes are inexpensive to acquire and retailers base their inventory systems on barcodes, there are operational incentives to associate distinct varieties with unique barcodes. Also, because barcode allocation is globally managed through the non-profit company GS1, two different firms will not be able to sell two different varieties under the same barcode. Second, alongside price information, scanner data also record physical quantities consumed. This is essential to estimate a structural model of demand and separate spatial differences in tastes from spatial differences in prices and product availability. Finally, within the selected categories, the scanner data provide a complete picture of the overall consumption basket. This makes it possible to identify both purely local and widely available varieties.[8] As countries rely on the same barcode system, we can credibly exploit within and between country variation in overall consumption baskets.

Firms As discussed, we refer to barcodes as distinct varieties. However, firms may sometimes deliberately offer different barcodes across countries for very similar (or even identical) varieties to limit parallel imports by distributors, or distributors may attach different barcodes when they repackage products before selling them to final consumers. Hence, relying solely on the set of common barcodes across countries could overestimate product availability differences between countries. To address this issue, we rely on data from GS1 that links barcodes to firm identifiers. This allows us to study differences in product availability at both the variety and the firm level.[9] Using this data, we associate a firm with a barcode for about 75% to 85% of all expenditures depending on the country (see Table A.2).[10] To check the quality of the firm identifier, we replicate the descriptive statistics on the firm size distribution documented by Hottman et al. (2016) in Tables A.3 - A.6. We find that these empirical patterns are very similar across countries and closely replicate the patterns reported by Hottman et al. (2016) for US scanner data.

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a smaller 8-digit identifier.

[7]In the EU, barcode descriptions are provided by the local affiliate of the market research firms. In a limited number of cases the exact barcode description for identical barcodes differs across countries. We treat this as measurement error and associate each barcode with one common package size across countries.

[8]This is in stark contrast to the set of papers that rely on international trade data to study the relationship between market integration and product availability (e.g. Broda & Weinstein (2006), Kehoe & Ruhl (2013) and Cavallo et al. (2022)). International trade data usually provides a detailed picture of the available traded varieties. But this does not include non-traded varieties which can be an important part of domestic consumption (see Eaton et al. (2011)). Matching trade and domestic sales data is hard because of different industry classifications (see Amiti et al. (2019) for an approach).

[9]See Hottman et al. (2016) for a similar approach and appendix A.3 for more detail on our exact procedure.

[10]When we cannot allocate a firm identifier this is usually because the barcode does not follow the 13-digit EAN standard or because it does not have an associated brand. Non-standard 13-digit codes are prevalent in Belgium, Germany, and the Netherlands in categories that contain a large share of fresh produce, e.g. fresh vegetables, fresh meat, etc.

Stores As mentioned before, the transaction data also record the retail chain at which the purchase was made. There are roughly six store types. Grocery stores (e.g. Carrefour Hyper, Hyper U) and hypermarkets (e.g. GB, Super U) are respectively mid-sized and large supermarkets, selling both food and non-food products. Discounters are stores with an everyday low-price strategy (e.g. Aldi, Lidl). Convenience stores are smaller stores with a limited assortment and focus on quick purchases. This group consists of the small store formats of larger retail chains (e.g. Carrefour Express, U Express), kiosks (e.g. 7-Eleven, Relay), and petrol stations (e.g. Total, Esso). Drugstores focus mostly on non-food items and are often chains (e.g. Hema, MAC, KIKO). Finally, specialist stores tend to stock a limited number of categories (e.g. bakers, liquor stores, butchers) and are often small and independent. We exclude cross-border transactions and online purchases that were made at an online retailer with no brick-and-mortar counterpart. Table A.8 provides an overview of the importance of the different stores across countries and shows that most purchases are made at brick-and-mortar stores. After omitting cross-border transactions and online purchases, we are left with a very comprehensive picture of overall consumption baskets within the selected categories.

Geographic data To account for geographic differences across NUTS2 regions, we complement the consumption data with geographical data from additional data sources. First, we use concordance tables from Eurostat to match ZIP codes and regions to their corresponding NUTS-2 level. In addition, we use data from Eurostat's GISCO services and from the US Counties database from simplemaps.com to obtain longitudes and latitudes for each of the ZIP codes.[11] We determine the population-weighted centroids of each region and compute great circle distances between them. Second, we use the ruggedness measures constructed in Nunn & Puga (2012) to measure whether regions differ in terms of the ruggedness of the terrain they entail.

3 Reduced-form evidence

This section documents that differences in prices and product availability are considerably larger between EU countries than within. These differences are also much larger than the differences between USA states. Taken together, this motivates the development of a unifying framework to measure the relative importance of both manifestations of market segmentation in section 4.

3.1 Price and product availability differences

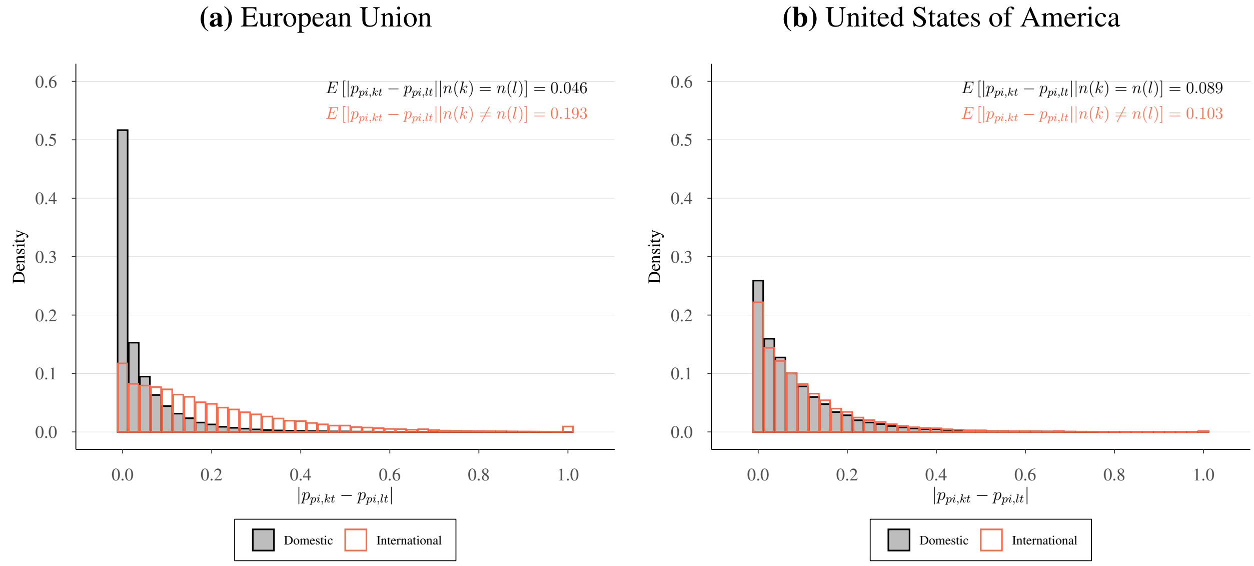
Price differences Given that aggregated price data typically overstate between country differences (Broda & Weinstein (2008) and Gorodnichenko & Tesar (2009)), we start by documenting LOP deviations at the variety level. To compute LOP deviations we first calculate average prices per variety for each European and US region and year. For each variety and year, we then compute the log price differences between all region pairs for which there exists a price observation. We do

[11] simplemaps.com combines data from the US Census Bureau and the Bureau of Labor Statistics.

this separately for the EU and the USA. To focus on the size of these price differences, we take the absolute value and consider absolute LOP deviations.[12] Furthermore, because we are interested in the question of whether the price differences are larger between countries (or states) than within them, we compare the distribution of absolute LOP deviations between international and domestic region pairs. For the USA, "international" and "domestic" region pairs refer to region pairs of different and the same states.

Figure 1 presents the conditional distributions of the absolute LOP deviations for international and domestic region pairs. Figure 1a focuses on the EU and Figure 1b on the USA. Within EU countries, many absolute price differences are close to zero and the average absolute LOP deviation is 4.6%. Between EU countries, the share of near zero LOP deviations is much smaller and the average absolute LOP deviation is 19.3%. In contrast, the distributions of absolute price differences between and within US states closely overlap, and LOP deviations are only around 1.4% larger between than within US states. Appendix B shows that the same patterns hold for subsamples of only branded and private label varieties and only branded varieties. In addition, computing LOP deviations by only using price observations within the same retail chain has no bearing on the results.

Figure 1: LOP deviations



Notes: This figure plots the conditional distributions of absolute LOP deviations for all EU and US region pairs in panels 1a and 1b respectively. The unit of observation is a variety-year- region pair. We bin the absolute LOP deviations into 40 separate bins and compute for each bin the number of transactions that fall into each bin. Finally, we right-censor the absolute deviations at 1 log point. The dark grey bars plot the distribution for domestic region pairs and the light grey bars do the same for international pairs. For each conditional distribution, we show the associated conditional mean value in the top-right corner in a color in accordance with the plots.

Differences in product availability The set of varieties for which we could compute LOP deviations between European international region pairs is quite small relative to the total set of

[12]Without data on production locations, the sign of price differences is not determined. However, the size of price differences is determined.

varieties in each of the regions. To explore this, we now look at product availability differences by computing two intuitive measures: one measure based on counts, the other on expenditures. First, consider the variety level. Define $\mathcal{B}_{p,lt}$ as the set of the consumed varieties in region l at time t in category p, and $\mathcal{B}_p^{kl}$ as the set of varieties that are available in both region l and region k over all periods, i.e. $\mathcal{B}_p^{kl} \equiv (\cup_{t=2010}^{2019}\mathcal{B}_{p,kt}) \cap (\cup_{t=2010}^{2019}\mathcal{B}_{p,lt})$.[13] The counts- and expenditure-based availability measures are then defined as follows at the variety level:

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

where $E_{pfi,lt}$ is the expenditure on variety i supplied by firm f in category p in location l at time t. The availability measures have bounded support between zero and one: if any two regions consume only common varieties, the measures are zero; if they have no varieties in common, the measures are one.

Now, consider the firm level. Define $\mathcal{F}_{p,lt}$ as the set of the firms selling in region l at time t, and $\mathcal{F}_p^{kl}$ as the set of firms that sell to both region l and region k in category p over all periods, i.e. $\mathcal{F}_p^{kl} \equiv (\cup_{t=2010}^{2019}\mathcal{F}_{p,kt}) \cap (\cup_{t=2010}^{2019}\mathcal{F}_{p,lt})$. The two availability measures at the firm level are then analogously defined as follows:

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

where $E_{pfi,lt}$ and is the expenditure on firm f in category p in location l at time t.

Figure 2 shows the conditional distributions of the count-based availability measures across region pairs and years. Figures 2a and 2c plot these distributions for the European region pairs. This shows there is limited overlap between the distributions for international and domestic region pairs. According to Figure 2a, domestic region pairs have on average 79% of varieties in common, whereas international region pairs have on average only 9% of varieties in common. According to Figure 2c, the difference between the distributions of international and domestic region pairs is somewhat smaller at the firm level, but it remains stark: domestic region pairs have on average 83% of firms in common, while international pairs have on average 19% of firms in common.

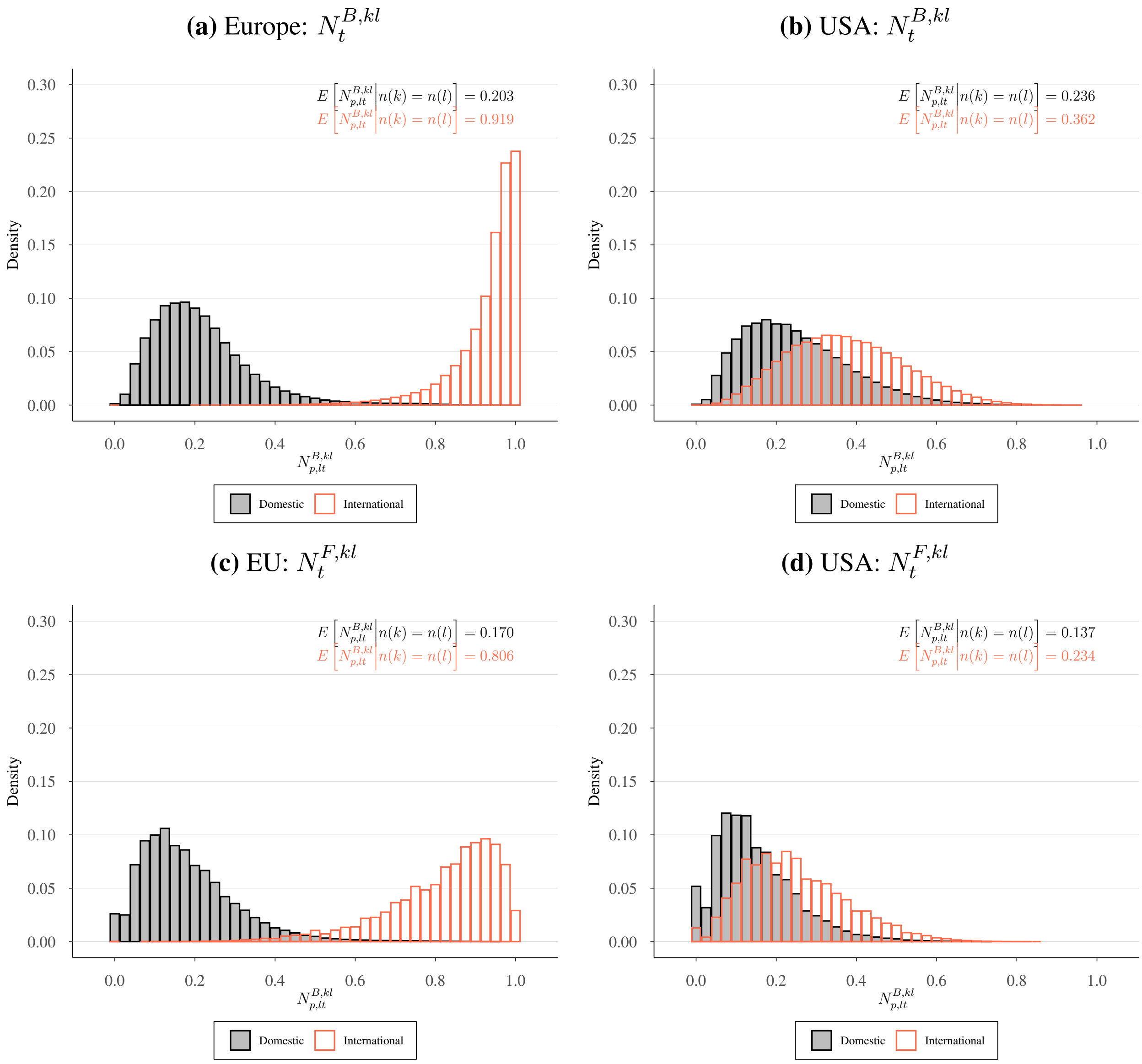
Figures 2b and 2d plot the distributions for US regions. This reveals a very different picture, in line with the results for LOP deviations. "Domestic" region pairs (i.e. pairs within the same US state)

[13] There are two relevant dimensions to define this union. First, one could define the set of common varieties as a time-varying set (see e.g. Broda & Weinstein (2010); Redding & Weinstein (2020)) or as a set that does not vary across time (e.g. Argente et al. (2021)). Second, one could define the set of common varieties at the country (e.g. Broda & Weinstein (2010); Redding & Weinstein (2020)) or at the regional level (e.g. Handbury & Weinstein (2015); Feenstra et al. (2020)). Because our data is sampled from household-level surveys, not observing a particular variety could be because it is not available or because it was not consumed even though it was available. To avoid misclassifying available varieties as unavailable, we consider a variety as unavailable when it was not consumed by any of the households over the 10 years of data we include. We also define the set of common varieties at the regional level to allow for within-country variation in choice sets across regions. Nevertheless, the results are robust and even become more pronounced under the time-varying and country-level definitions.

have on average 76% of varieties in common, while "international" region pairs (from different US states) still have 64% of varieties in common. Furthermore, domestic and international region pairs have respectively 86% and 77% of firms in common.

In sum, in the EU the product availability differences are much stronger between countries than within countries, while in the US the availability differences are more comparable between and within states. Appendix B shows that the same patterns hold for the expenditure-based availability measures, and for subsamples of only branded and private labels and only branded varieties.

Figure 2: Differences in product availability: Count-based



Notes: This figure plots the distribution for the count-based product availability measures across region pair-year observations. The dark grey bars plot the distribution for domestic region pairs and the light grey bars do the same for international pairs. Figures 2a and 2c plot the variety- and firm-level measures for Europe. Figures 2b and 2d show the variety- and firm-level measures for the USA. For each distribution, we show the associated conditional mean value in the top-right corner in a color in accordance with the plots.

3.2 Distance versus borders

Apart from cross-border geographic market segmentation, geographic factors may also explain why LOP deviations and product availability differences are larger for international than domestic region pairs. To disentangle geographic factors from country borders, we estimate border effects separately for European and US regions using a very similar specification as McCallum (1995) and Engel & Rogers (1996). More specifically, we estimate:

$$y_{pi,t}^{kl} = \beta \ln \left(\text{Distance}^{kl}\right) + \gamma B^{kl} + \theta_l + \theta_k + \lambda_{p,t} + \varepsilon_{pi,t}^{kl} \tag{1}$$

where $y_{pi,t}^{kl}$ is either the variety-level LOP deviation or one of the measures for product availability differences. B^{kl} is a dummy variable equal to one when region pair kl is an international pair and zero otherwise, and Distance^{kl} is the population-weighted great circle distance between the regions. We add region fixed effects θ_l and θ_k to account for the fact that certain regions might be characterized by always higher price dispersion or product availability differences and add category-year fixed effects to focus on cross-sectional variation.

Table 1 provides the results of estimating Equation 1 for EU regions in panel (a) and for US regions in panel (b). First, columns (1) and (2) show the results for absolute LOP deviations. According to column (1), which does not control for distance, price dispersion is roughly 17% higher between EU countries than within EU countries. In contrast, price dispersion is on average only 1.5% higher between US states than within US states. However, price dispersion could also increase with distance between regions. Column (2) confirms that price dispersion indeed increases with the distance between both EU and US regions. While controlling for distance reduces the border effect between US states by almost an order of magnitude (from 1.5% to 0.35%), the border effect between EU regions remains almost unchanged. Even conditional on distance between regions, absolute LOP deviations remain about 16% larger between EU regions than within them.

Second, in line with our earlier Figure 2, product availability differences are larger between international region pairs relative to domestic region pairs. Columns (3), (5), (7) and (9) show that, depending on the measure, differences in product availability are 70% and 74% larger at the variety level and 47% and 67% larger at the firm level between EU countries than within EU countries. In the US, the difference in product availability differences is only 11% and 12% at the variety level and 4% and 9% at the firm level, depending on the measure. To understand whether this border effect also partially captures the effect of distance between regions, columns (4), (6), (8) and (10) additionally control for the distance between regions. As with price dispersion, conditional on distance, the estimated differences in product availability between EU countries relative to within EU countries remain very close to the unconditional estimates. However, controlling for the distance between US regions reduces the estimated differences in product availability differences by an order of magnitude. While the count-based product availability differences are reduced to a little over 1% conditional on the distance between regions, the expenditure-based measures are barely significantly different from zero.

Finally, to see whether price and product availability converged over time, i.e. that LOP deviations and product availability differences declined over the considered period, we also estimated a more restrictive version of Equation 1 with category fixed effects λ_p and a trend variable. Table B.3 shows that the coefficients reported in Table 1 remain virtually identical and that the trend variable is quantitatively very small (although often statistically significant). Altogether, there is little evidence of convergence in price and product availability from 2010 to 2019 in both the EU and the US. This motivates the cross-sectional focus in the rest of the paper.

Taking stock, conditional on geographic distance, price and product availability differences between US states are quite similar to differences within US states. In stark contrast, differences in price and product availability between European countries are much greater relative to within EU country differences. There are, however, two open questions. First, how do the variation in price differences and product availability differences quantitatively compare? Second, does the variation in prices and product availability map into the presence of variable and fixed trade frictions and thus the presence of cross-border market segmentation? In the next section, we design a two-step approach to answer these questions and detect cross-border geographic market segmentation.

4 Empirical Framework: Two-step approach

The empirical approach to detecting the sources of cross-border market segmentation consists of two steps. In the first step, we borrow from the literature on estimating cost-of-living differences and describe how assumptions about consumer behavior allow us to measure regional cost-of-living differences, and to decompose these into taste differences, LOP deviations, and differences in product availability.[14] Crucially, this step delivers a measurement of the two manifestations of geographic market segmentation, LOP deviations and differences in product availability, in terms of a common unit which enables us to compare their relative magnitude. In the second step, we design a spatial differencing strategy in which we compare price and product availability differences between countries to price and product availability differences within countries. We show that under certain assumptions on technology and the market environment, this strategy permits us to separate the presence of cross-border geographic market segmentation from natural variation in prices and product availability differences due to transport costs.

4.1 Regional cost-of-living differences

Consumer preferences Within each region consumers derive utility from a triple nested utility system. We assume that the final good aggregator is separable across the set of categories $\mathcal{P}$, but because we consider category-level cost-of-living differences we leave its particular functional form

[14]To stay close to the literature on cost-of-living differences and to avoid confusion, we will refer to differences in unit expenditure as cost-of-living differences even though our data only represents a part of the CPI basket.

Table 1: Border effects: Price and product availability differences

y_{klt}	$\lvert p_{pi,kt} - p_{pi,lt}\rvert$		$N_{lt}^{B,kl}$		$\lambda_{lt}^{B,kl}$		$N_{lt}^{F,kl}$		$\lambda_{lt}^{F,kl}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PANEL (A): EUROPE										
Border^{kl}	.1712***	.1621***	.7438***	.7081***	.7955***	.7539***	.6707***	.6441***	.4729***	.4459***
	(.0011)	(.0012)	(.0024)	(.0028)	(.0021)	(.0026)	(.0027)	(.0032)	(.0028)	(.0032)
ln (Distance)^{kl}		.0069***		.0444***		.0518***		.0331***		.0336***
		$(3.4e-04)$		(.0022)		(.0023)		(.0025)		(.0024)
Domestic	.046	.046	.203	.203	.1319	.1319	.17	.17	.0263	.0263
Nr. obs	34,082,536	34,082,536	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670
Within R^2	0.04	0.04	0.94	0.94	0.93	0.93	0.90	0.90	0.67	0.67
PANEL (B): UNITED STATES OF AMERICA										
Border^{kl}	.0152***	.0035***	.1202***	.0152***	.111***	.0049*	.0972***	.0107***	.0411***	-.002
	$(6.7e-04)$	$(6.5e-04)$	(.0037)	(.0025)	(.0038)	(.0027)	(.0035)	(.003)	(.0016)	(.0016)
ln (Distance)^{kl}		.0068***		.0613***		.062***		.0506***		.0252***
		$(2.3e-04)$		$(5.8e-04)$		$(6.2e-04)$		$(5.0e-04)$		$(3.2e-04)$
Domestic	.0887	.0887	.203	.2364	.1387	.1387	.1366	.1366	.015	.015
Nr. obs	123,914,760	123,914,760	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360
Within R^2	0.00	0.00	0.07	0.29	0.04	0.18	0.04	0.17	0.01	0.07
θ_l	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
θ_l	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$\lambda_{p,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents the results from Equation 1 with OLS. Panel (a) presents the results for European regions and panel (b) for US regions. Columns (1)-(2) present the results for the variance of LOP and columns (3)-(10) show the results for various measures of product availability differences. Columns (3)-(6) focus on the variety-level and columns (7)-(10) provide estimates for the firm level measures of product availability measures. Columns (3), (5),(7) and (9) show count-based estimates. Columns (4), (6),(8) and (10) show count-based estimates. Alongside the estimates, we provide the average value of the left-hand variable for domestic regions under “Domestic”, the number of observations and the R^2 of the regression after partialling out the fixed effects. We cluster standard errors at the region pair and present them in brackets below the coefficient estimates. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

unspecified:

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

where $F_{lt}(\cdot)$ is the final good aggregator which can be region-specific and time-varying (e.g. a Cobb-Douglas aggregator). $C_{p,lt}$ is the consumption level in region l of category p at time t. Consumption bundles $C_{p,lt}$ comprise two CES-utility nests that sequentially aggregate the consumption of individual varieties.

In the middle nest, consumers allocate $C_{p,lt}$ to different firms, denoted by f, that supply at least one variety in that category and region subject to the following aggregator:

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

where $\Omega_{p,lt}$ is the set of firms that supply at least one variety in category p in region l at time t and $C_{pf,lt}$ is the firm-level consumption level. We refer to $\xi_{pf,lt}$ as consumer taste for firm f in category p in region l at time t. In principle, $\xi_{pf,lt}$ represents both horizontal differentiation, or taste, and vertical differentiation, or product quality. As we compare spatial variation in prices and consumption levels of the identical varieties, we interpret $\xi_{pf,lt}$ as consumer taste. Finally, η_p denotes the constant elasticity of substitution across firms, which is allowed to vary across categories.

In the lower nest, consumers allocate $C_{pf,lt}$ to individual varieties, denoted by i, subject to another CES-utility aggregator:

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

where $\Omega_{pf,lt}$ is the set of varieties supplied by firm f in category p in region l at time t and $C_{pfi,lt}$ is the variety-level consumption level. $\xi_{pfi,lt}$ captures consumer taste for variety and σ_p is the elasticity of substitution across varieties, which is also allowed to vary across categories.[15] Because the utility function is homogeneous of degree 1 in firm-level consumer tastes, it is impossible to distinguish between changes in firm-level consumer tastes $\xi_{pf,lt}$ and changes in variety-level consumer tastes $\xi_{pfi,lt}$. It will prove convenient to normalize the geometric average of $\xi_{pfi,lt}$ across all varieties provided by firm f in region l to be time-invariant:

$$\tilde{\xi}_{pf,lt} \equiv \left(\prod_{i\in\Omega_{pf,lt}} \xi_{pfi,lt}\right)^{\frac{1}{N_{pf,lt}}} = \left(\prod_{f\in\Omega_{pf,lt+1}} \xi_{pfi,lt+1}\right)^{\frac{1}{N_{pf,lt+1}}} \equiv \tilde{\xi}_{pf,lt+1}. \tag{2}$$

where $N_{pf,lt} \equiv |\Omega_{pf,lt}|$.[16] Under this normalization, shifts in consumer taste in region l affecting all

[15] The consumption level $C_{pfi,lt}$ enters symmetrically for branded and private label products in the preference system. For private label products, the retailer that offers the product is considered to be a firm, and the individual product enters as a variety.

[16] Hottman et al. (2016) consider a very similar normalization by putting them equal to 1 at all times.

varieties equally are captured through changes in $\xi_{pf,lt}$, and relative changes in consumer taste across varieties supplied by the same firm are captured by relative changes in $\xi_{pfi,lt}$.

Cost-of-living level If consumers minimize expenditure, conditional on the utility level they wish to attain, then the associated unit expenditure functions at the category and firm level are given by:

$$P_{p,lt} = \left(\sum_{f \in \Omega_{p,lt}} \left(\frac{P_{pf,lt}}{\xi_{pf,lt}} \right)^{1-\eta_p} \right)^{\frac{1}{1-\eta_p}}, \qquad P_{pf,lt} = \left(\sum_{i \in \Omega_{pf,lt}} \left(\frac{P_{pfi,lt}}{\xi_{pfi,lt}} \right)^{1-\sigma_p} \right)^{\frac{1}{1-\sigma_p}}, \tag{3}$$

where $P_{pfi,lt}$ is the price of variety i in region l at time t. Because the utility functions are homothetic, differences in the cost of living across regions can be studied through differences in the unit expenditure functions.

Decomposing cost-of-living differences To decompose cost-of-living differences between any two regions k and l, we start at the firm level and define the expenditure share spent on firms that sell to region k and region l in category p relative to all expenditure in region l in category p, $\lambda^{kl}_{p,lt}$, and the common market share of firm f in category p, $S^{kl}_{pf,lt}$, as:

$$\lambda^{kl}_{p,lt} \equiv \frac{\sum_{f \in \Omega^{kl}_p} P_{pf,lt} C_{pf,lt}}{\sum_{f \in \Omega_{p,lt}} P_{pf,lt} C_{pf,lt}}, \qquad S^{kl}_{pf,lt} \equiv \frac{P_{pf,lt} C_{pf,lt}}{\sum_{f \in \Omega^{kl}_p} P_{pf,lt} C_{pf,lt}},$$

where $\Omega_{p,lt}$ is the set of firms selling to region l in category p at time t, and Ω^{kl}_p is the set of firms that sell both to region k and region l in category p, i.e. $\Omega^{kl}_p \equiv (\cup^{2019}_{t=2010} \Omega_{p,kt}) \cap (\cup^{2019}_{t=2010} \Omega_{p,lt})$. Together these two objects make up the market share in region l at time t, $S_{fp,lt}$, of firms selling to both regions k and l: $S_{fp,lt} = S^{kl}_{pf,lt} \cdot \lambda^{kl}_{p,lt} \; \forall \; f \in \Omega^{kl}_p$. Combining these expressions allows us to derive the following expression for the difference in the category-level cost-of-living between regions k and l:

$$\ln\left(\frac{P_{p,kt}}{P_{p,lt}}\right) = \frac{1}{N^{kl}_p} \sum_{f \in \Omega^{kl}_p} \left[\ln\left(\frac{P_{pf,kt}}{P_{pf,lt}}\right) - \ln\left(\frac{\xi_{pf,kt}}{\xi_{pf,lt}}\right) + \frac{1}{\eta_p - 1} \ln\left(\frac{S^{kl}_{pf,kt}}{S^{kl}_{pf,lt}}\right) \right] + \frac{1}{\eta_p - 1} \ln\left(\frac{\lambda^{kl}_{p,kt}}{\lambda^{kl}_{p,lt}}\right). \tag{4}$$

Equation 4 is composed of two parts. The first part captures cost-of-living differences between regions l and k that stem from price and taste differences. This first part intuitively starts with the ratio of the unweighted geometric average price levels of common goods between regions k and l, i.e. $\tilde{P}^{kl}_{p,kt} / \tilde{P}^{kl}_{p,lt}$, where $\tilde{P}^{kl}_{p,kt} \equiv \prod_{f \in \Omega^{kl}_p} (P_{pf,kt})^{1/N^{kl}_p}$: if the price level for common goods is higher in region k, then the cost of living in region k should be higher as well. However, there are two correction terms. The first correction term is the ratio of the unweighted average taste levels between regions k and l, i.e. $\tilde{\xi}^{kl}_{p,kt} / \tilde{\xi}^{kl}_{p,lt}$, where $\tilde{\xi}^{kl}_{p,kt} \equiv \prod_{f \in \Omega^{kl}_p} (\xi_{pf,kt})^{1/N^{kl}_p}$. We make the normalization assumption that these average taste differences between regions are zero, i.e. $\tilde{\xi}^{kl}_{p,kt} = \tilde{\xi}^{kl}_{p,lt}$. As such, this rules out cost-of-living differences that solely reflect differences in the average level of consumer tastes of firms that sell to both regions. Redding & Weinstein (2020) impose a similar restriction on average taste levels over time.[17] The second correction term is the difference in the unweighted average of firm-level common market shares across regions. It captures how, despite zero average taste differences, firm-specific taste differences between regions may affect cost-of-living differences: a high price for one firm does not necessarily imply a high cost of living if the taste for that firm is high, as reflected in a lower geometric average market share (unless firms are perfect substitutes, i.e. $\eta_p \rightarrow \infty$).[18] In sum, the first part of Equation 4 captures average cost-of-living differences between two regions stemming from average price differences of common goods, after adjusting for firm-specific taste differences.

The second part of Equation 4 accounts for differences in product availability across regions. For a given elasticity of substitution, η_p, a lower expenditure share on common firms in a certain region k ($\lambda^{kl}_{p,kt}$) corresponds to a lower cost of living. Intuitively, this indicates that consumers in that region allocate a greater share to alternatives not available elsewhere. This represents a higher welfare and therefore a lower cost of living. The magnitude of the product availability term depends on the elasticity of substitution η_p. If η_p is high, bundles are considered close substitutes, and additional alternatives add little additional gains, resulting in a small welfare effect from differences in product availability.

At the moment, Equation 4 still depends on the unobserved firm-level price indices $P_{pf,kt}$. To further decompose them, we follow similar steps.[19] Taking logs, and adding and subtracting $\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t} \left[\sum_{i\in\Omega^{kl}_{pf}} \omega^{kl}_{pfi,t} \ln\left(\frac{P_{pfi,kt}}{P_{pfi,lt}}\right)\right]$ from Equation 4 results in our final decomposition of

[17] This normalization is necessary because we observe only choices given the available set of products and their prices, and not the underlying utility levels. Hence, if prices, product availability, and choices are all identical across regions, so should cost-of-living levels be. Alternatively, we could have normalized the taste of one particular firm across the different regions. However, it is non-trivial to determine which firm could have the same taste level across regions are mean zero.

[18] This term extends beyond the well-known Sato-Vartia index. Appendix C.1 provides further intuition for this generalization.

[19] Similar to the category-level normalization assumption $\tilde{\xi}^{kl}_{p,kt} = \tilde{\xi}^{kl}_{p,lt}$, we make the firm-level normalization assumption $\tilde{\xi}^{kl}_{pf,kt} = \tilde{\xi}^{kl}_{pf,lt}$, where $\tilde{\xi}^{kl}_{pf,kt} \equiv \prod_{f\in\Omega^{kl}_{pf}} \left(\xi_{pfi,kt}\right)^{1/N^{kl}_{pf}}$.

category-level cost-of-living differences between regions k and l:

$$\underbrace{\ln\left(\frac{P_{p,kt}}{P_{p,lt}}\right)}_{(P^{kl}_{p,t})} = \underbrace{\frac{1}{N^{kl}_p}\sum_{f\in\Omega^{kl}_{pf}}\left[\frac{1}{N^{kl}_{pf}}\sum_{i\in\Omega^{kl}_{pf}}\ln\left(\frac{P_{pfi,kt}}{P_{pfi,lt}}\right)\right] - \sum_{f\in\Omega^{kl}_p}\omega^{kl}_{pf,t}\left[\sum_{i\in\Omega^{kl}_{pf}}\omega^{kl}_{pfi,t}\ln\left(\frac{P_{pfi,kt}}{P_{pfi,lt}}\right)\right]}_{\text{Taste differences } (T^{kl}_{p,t})}$$

$$+\underbrace{\frac{1}{N^{kl}_p}\sum_{f\in\Omega^{kl}_p}\left[\frac{1}{\eta_p-1}\ln\left(\frac{S^{kl}_{pf,kt}}{S^{kl}_{pf,lt}}\right) + \frac{1}{\sigma_p-1}\frac{1}{N^{kl}_{pf}}\sum_{i\in\Omega^{kl}_{pf}}\ln\left(\frac{S^{kl}_{pfi,kt}}{S^{kl}_{pfi,lt}}\right)\right]}_{\text{Taste differences } (T^{kl}_{p,t}) \text{ - ctd.}}$$

$$+\underbrace{\sum_{f\in\Omega^{kl}_p}\omega^{kl}_{pf,t}\left[\sum_{i\in\Omega^{kl}_{pf}}\omega^{kl}_{pfi,t}\ln\left(\frac{P_{pfi,kt}}{P_{pfi,lt}}\right)\right]}_{\text{LOP deviations + Substitution Effect } (L^{kl}_{p,t})} + \underbrace{\frac{1}{\eta_p-1}\ln\left(\frac{\lambda^{kl}_{p,kt}}{\lambda^{kl}_{p,lt}}\right) + \frac{1}{\sigma_p-1}\frac{1}{N^{kl}_p}\sum_{f\in\Omega^{kl}_p}\ln\left(\frac{\lambda^{kl}_{pf,kt}}{\lambda^{kl}_{pf,lt}}\right)}_{\text{Differences in product availability} (\Lambda^{kl}_{p,t})} \tag{5}$$

where

$$\omega^{kl}_{pf,t} \equiv \frac{\frac{S^{kl}_{pf,kt}-S^{kl}_{pf,lt}}{\ln S^{kl}_{pf,kt}-\ln S^{kl}_{pf,lt}}}{\sum_{f\in\Omega^{kl}_p}\frac{S^{kl}_{pf,kt}-S^{kl}_{pf,lt}}{\ln S^{kl}_{pf,kt}-\ln S^{kl}_{pf,lt}}}, \qquad \omega^{kl}_{pfi,t} \equiv \frac{\frac{S^{kl}_{pfi,kt}-S^{kl}_{pfi,lt}}{\ln S^{kl}_{pfi,kt}-\ln S^{kl}_{pfi,lt}}}{\sum_{i\in\Omega^{kl}_{pf}}\frac{S^{kl}_{pfi,kt}-S^{kl}_{pfi,lt}}{\ln S^{kl}_{pfi,kt}-\ln S^{kl}_{pfi,lt}}},$$

This expression shows that regional cost-of-living differences can be decomposed into (1) pure taste differences, (2) weighted average LOP deviations and (3) differences in product availability. The first part, $T^{kl}_{p,t}$, captures pure taste differences at the firm and variety levels, and is the cross-sectional analog of the taste-bias term derived by Redding & Weinstein (2020). More precisely, this term is defined as the difference between the generalized price index, which is valid under differences in consumer taste, and the Sato-Vartia price index, which holds in the absence of taste differences. The second part of Equation 5, given by $L^{kl}_{p,t}$, is the Sato-Vartia price index which captures LOP deviations, aggregated to represent the relative importance of each variety in the consumption baskets of consumers in region k and l. The final part of Equation 5, denoted by $\lambda^{kl}_{pf,lt}$, captures differences in choice sets between regions k and l at the firm and variety level, for the set of firms selling to both regions.

The above analysis is based on a nested CES demand system, but generalizes to other widely-used demand systems. As the obtained decomposition of cost-of-living differences is the cross-sectional variant of the one developed in Redding & Weinstein (2020), similar decompositions hold for non-homothetic CES, Mixed-CES, Logit, AIDS and Translog demand systems.

4.2 Spatial differencing

The first step of our two-step approach provides a decomposition of cost-of-living differences in three terms. As such, this allows us to measure the two manifestations of cross-border market segmentation, international differences in prices and product availability, in a common unit and to filter out taste differences between countries (or states). However, international price and product availability differences may not only be driven by cross-border market segmentation but also by other natural trade frictions, such as transport costs. To isolate cross-border trade frictions from other trade frictions, we design a spatial differencing strategy that compares particular variation in prices and product availability between and within countries.

Identification challenge To understand the identification challenge in separating cross-border trade frictions from other natural trade frictions, we introduce additional notation. As before, consider B^{kl} as the indicator variable that is 1 if kl is an international region pair, and zero if kl is a domestic region pair. Given this, define the potential outcomes as follows:

$$Y_{p,t}^{kl} = \begin{cases} Y_{p,t}^{kl}(1) & \text{if } B^{kl} = 1, \\ Y_{p,t}^{kl}(0) & \text{if } B^{kl} = 0. \end{cases}$$

where $Y_{p,t}^{kl}(1)$ is the potential outcome in product category p at time t if kl is an international region pair, and $Y_{p,t}^{kl}(0)$ is the potential outcome when kl is a domestic region pair. We consider the outcome variables, $Y_{p,t}^{kl} = \{P_{p,t}^{kl}, T_{p,t}^{kl}, L_{p,t}^{kl}, \Lambda_{p,t}^{kl}\}$, i.e. cost-of-living differences, and its three components. The latter two, LOP deviations and product availability differences, are the manifestations of market segmentation.

If production region and transportation routes are observed, one may disentangle border-related frictions from other frictions by comparing outcomes in two regions on either side of the border.[20] Figure 3a illustrates this strategy. Suppose that we observe that goods are produced in region z and consumed in region k. If $B^{kz} = 1$, kz is an international region pair; if $B^{kz} = 0$, kz is a domestic region pair. As long as the geographic differences between the domestic and international region pair are similar, i.e. $\boldsymbol{X}^{kz} = x$, one can assess cross-border segmentation by comparing the potential outcomes between international region pairs and domestic region pairs to control for differences that are induced by transport costs.

There are two reasons why this identification strategy is unfit for our dataset. First, we observe neither the production regions, nor the transportation routes. Hence, we have to treat z as unobserved. Figure 3b presents this case by indicating the unobserved transportation routes from z to the consumption locations, such as l and k. Figure 3b also illustrates that we can now construct outcomes as differences between only consumption locations kl, such as a domestic region pair if $B^{kl} = 0$ or an international region pair if $B^{kl} = 1$. By constructing outcomes as differences between two consumption locations, we have to deal with the fact that it is conceptually equally appropriate to construct outcomes by taking the difference between k and l or l and k. While the sign of the differences in the outcomes is undetermined, the size of the differences remains determined, and so we will compare the absolute value of the differences.

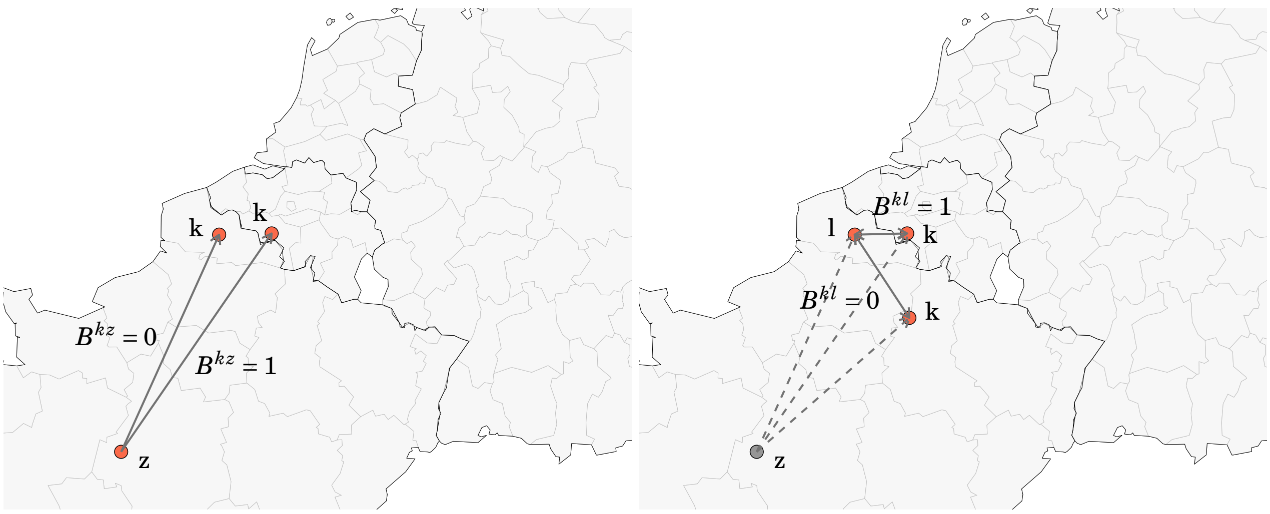
Second, the condition, $\boldsymbol{X}^{kl} = x$ for both $B^{kl} = 1$ and $B^{kl} = 0$, is no longer sufficient to control

[20] Santamaria et al. (2020) recently applied such a strategy to differences in between- and within-country trade shares.

for differences in transport costs when production locations are unobserved. First, by considering absolute instead of simple differences, differences in transport costs no longer necessarily cancel out. Furthermore, we are considering aggregate outcome variables at the category level (given our aim to measure price and product availability differences in a common unit). This is an aggregation over varieties with potentially heterogeneous differences in transport costs. Therefore, even if we were to consider simple differences, differences in transport costs will not necessarily cancel. To overcome these issues, we focus attention on region pairs that are geographically close, i.e. $\boldsymbol{X}^{kl} = 0$. Intuitively, transport costs between regions will then be similar and difference out. Proposition 1 formalizes that, under additional restrictions on the economic environment, comparing price and product availability differences among geographically close regions is sufficient to detect cross-border geographic market segmentation when transport costs are unobserved.

Figure 3: Identification challenge

(a) With information about transportation **(b)** Without information about transportation



Notes: This figure depicts two hypothetical scenarios. Figure 3a considers the case when we know that production takes place in z and consumption in k. Figure 3b depicts the case where consumption also takes place in l and k and the production region is in z, which is unobserved. Because production regions and transport routes are unobserved, we indicate the unobserved transportation routes in dashed lines.

Structural assumptions We restrict the economic environment in two ways. The first restriction applies to the production function. We assume that each firm can set up one plant in a region z, where it produces according to the following cost function:

$$\mathrm{C}_{pf,t} = \sum_{l \in \mathcal{L}} \sum_{i \in \Omega_{pfl,t}} \varphi_{pfi,zt} \cdot Q_{pfi,zt} + F_{pf,t} \cdot \mathbb{1}\left(\sum_{l \in \mathcal{L}} \sum_{i \in \Omega_{pfl,t}} Q_{pfi,zt} > 0 \right).$$

The cost function has a variable part that depends on the constant marginal cost of producing variety i at time t, $\varphi_{pfi,zt}$. The cost function also has a fixed part, $F_{pf,t}$, that is incurred if there is any quantity

$Q_{pfi,zt}$ produced. This fixed cost not only captures the costs of setting up a production plant but also the costs of creating a domestic distribution system that grants access to all regions in the country where the firm produces. Assuming no economies of scope nor economies of scale on the variable factors of production is restrictive, but standard in the trade literature on multi-product firms (see Eckel & Neary (2010), Bernard et al. (2011) and Mayer et al. (2014)). The distribution of $F_{pfz,t}$ is, however, left unrestricted, such that economies of scale can occur through the fixed costs of setting up production.[21]

The second restriction pertains to the market environment in which firms compete. There are two stages. Firms first decide whether to produce and in which regions to enter. Entering firms then compete in a monopolistically competitive environment in each region. Given the nested CES demand system, this yields the following optimal pricing rule:

$$P_{pfi,lt} = \mathcal{M}_{pfi,lt}\mathrm{MC}_{pfi,lt}, \qquad \text{where} \quad \mathcal{M}_{pfi,lt} = \frac{\varepsilon_{pfi,lt}}{\varepsilon_{pfi,lt} - 1} \quad \text{and} \quad \varepsilon_{pfi,lt} = \eta_p.$$

Here, $\mathcal{M}_{pfi,lt}$ is the markup charged for variety i in region l at time t, and $\mathrm{MC}_{pfi,lt}$ is the marginal cost of delivering variety i to region l. This marginal cost is given by:

$$\mathrm{MC}_{pfi,lt} = \varphi_{pfi,zt} t_{pfi,zt}\left(\boldsymbol{X}^{lz}\right)\tau_{pfi,t} B^{lz}$$

and consists of two components. First, there is the marginal cost of production $\varphi_{pfi,zt}$ of producing in region z. Second, there are trading frictions, which consist of transport costs $t_{pfi,zt}\left(\boldsymbol{X}^{lz}\right)$ that continuously depend on the geography traversed to arrive in region l, $\boldsymbol{X}^{lz}$, and cross-border trade costs $\tau_{pfi,t}$ incurred if $B^{lz} = 1$. The presence of $\tau_{pfi,t} > 1$ allows for LOP deviations beyond the costs of physically moving goods to the destination market. Conditional on producing domestically, firms decide whether to enter other countries and determine the set of varieties to offer:

$$\begin{aligned}\max_{\Omega_{pf,lt}} = & \sum_{l\in n}\sum_{i\in\Omega_{pfl,t}} \left(P_{pfi,lt} - \mathrm{MC}_{pfi,lt}\right) Q_{pfi,lt} \\ & - F^X_{pf,t} \cdot \mathbb{1}\left(\sum_{l\in n}\sum_{i\in\Omega_{pf,lt}} B^{zl} Q_{pfi,lt} > 0\right) - \sum_{i\in\Omega_{pf,lt}} F^X_{pfi,t} \cdot \mathbb{1}\left(\sum_{l\in n} B^{zl} Q_{pfi,lt} > 0\right)\end{aligned}$$

where $F^X_{pf,t}$ is a fixed cost to enter region l and $F^X_{pfi,t}$ is a fixed cost per variety supplied to region l. These costs capture, for instance, the costs associated with setting up distribution and allow us to capture differences in product availability both at the firm and variety levels. Like before, paying these costs grants access to all regions in that particular country.[22]

[21] Note that fixed costs of setting up a plant can differ across firms and across regions for a given firm. This represents one potential reason why similar firms might set up their plant in different regions.

[22] Section 3 highlighted that small differences in product availability exist for domestic region pairs but that they are especially pronounced for international region pairs. This particular set of assumptions, therefore, captures most of the variation in the data..

Detecting cross-border market segmentation We now show how one can detect the presence of cross-border market segmentation by comparing differences in absolute price and product availability differences between international and domestic region pairs. More specifically, the assumptions on demand, technology and the market environment have two implications. First, observing a positive difference in the absolute value of LOP deviations between international and domestic region pairs implies the presence of variable trade frictions. Second, observing a positive difference in the absolute value of product availability differences between international and domestic region pairs implies the presence of fixed trade frictions. Proposition 1 formalizes these two testable conditions:

Proposition 1 (Detecting cross-border market segmentation)**.** *Given the assumptions on demand, technology and the market environment, we have that:*

$$\gamma_L \equiv \mathbb{E}\Big[\,\big|L^{kl}_{p,t}(1)\big| - \big|L^{kl}_{p,t}(0)\big|\,\Big|B^{kl}=1, \boldsymbol{X}^{kl}=0\Big] > 0 \quad \Rightarrow \quad \exists\; \tau_{pfi,t} > 1$$
$$\gamma_\Lambda \equiv \mathbb{E}\Big[\,\big|\Lambda^{kl}_{p,t}(1)\big| - \big|\Lambda^{kl}_{p,t}(0)\big|\,\Big|B^{kl}=1, \boldsymbol{X}^{kl}=0\Big] > 0 \quad \Rightarrow \quad \exists\; F^X_{pf,t}, F^X_{pfi,t} > 0$$

Proof. See Appendix C.2 □

To gain further intuition, consider first the implication of $\gamma_L > 0$, i.e. a positive average difference in the absolute value of LOP deviations between international, $\big|L^{kl}_{p,t}(1)\big|$, and domestic region pairs, $\big|L^{kl}_{p,t}(0)\big|$, conditional on zero geographic differences. Under the structural assumptions, this particular differencing strategy differences out differences in transport cost and manufacturing markups. Hence, if a certain price is profit-maximizing in the firm's home country, where no cross-border variable trade frictions apply, no larger price is profit-maximizing elsewhere, unless there are positive variable cross-border trade frictions. Now consider the implication of $\gamma_\Lambda > 0$, i.e. a positive average difference in absolute product availability differences between international, $\big|\Lambda^{kl}_{p,t}(1)\big|$, and domestic region pairs, $\big|\Lambda^{kl}_{p,t}(0)\big|$. Under CES-demand, profits are always non-zero as the choke price is infinite. Hence, if it is profitable for a firm to enter or sell a given variety in its home country, it is also profitable to enter or offer a particular variety abroad, unless there are positive fixed cross-border trade frictions.

Proposition 1 also indicates that the differences in the absolute value of LOP deviations and product availability differences are only sufficient conditions to detect positive variable and fixed trade frictions. To see why the first condition is not necessary for the presence of variable trade costs, consider the knife-edge case in which tastes are homogeneous across locations, variable trade costs are positive but homogeneous across goods and locations and production locations are equally split between location k and l. In this case, average absolute LOP deviations between the two locations will be equal to zero as variable trade costs cancel out. Also, to see why the second condition is not necessary for the presence of fixed trade costs, consider a similar knife-edge case in which tastes are homogeneous across locations and fixed trade costs are positive but homogeneous across goods and locations The expenditure share on common varieties will then be equal in both locations (though less than one), and the absolute product availability differences will be equal to zero.

Role of the assumptions Our approach to detect cross-border market segmentation is reminiscent of the approach considered in Chari et al. (2007) or Hsieh & Klenow (2009) in that deviations from model-implied optimality conditions, i.e. first-order condition for prices and a free entry condition, are interpreted as variable and fixed cross-border trade frictions. As the uncovered frictions are model-dependent, a natural question is how broad the set of models is that would give rise to the same testable conditions spelled out in Proposition 1.

Many popular international trade models are contained within the set of assumptions on the economic environment. For instance, all models in the class considered in Arkolakis et al. (2012) are included. Among others, Armington-type models, e.g. Anderson & Wincoop (2003), Ricardian models, e.g. Eaton & Kortum (2002), Costinot et al. (2012) and Caliendo & Parro (2015) and increasing returns to scale models, e.g. Krugman (1980), Melitz (2003), Melitz & Redding (2015) and Antràs et al. (2017) all satisfy the assumptions on demand, technology, and market structure.

Furthermore, three assumptions to detect market segmentation can be relaxed: iceberg trade costs, monopolistic competition and single-plant production. First, the assumption of multiplicative (or iceberg) trade costs is innocuous. Appendix C.2 shows that the same arguments hold when the marginal cost of production and trade costs interact in general ways. For price differences between international and domestic region pairs, transport costs are still controlled for when the regions are all geographically close. Under CES preferences, fixed trade costs are still required to explain differences in product availability even when trade costs are not multiplicative.

Second, under monopolistic competition, manufacturing markups depend only on the firm-level elasticity of substitution, which is assumed to be the same across regions. In contrast, under oligopolistic competition, e.g. Atkeson & Burstein (2008) or Crowley et al. (2023), markups additionally depend on market shares which may differ across regions. In this case, looking at a difference in marginal cost differences would be sufficient to detect positive variable trade costs. We consider this below.

Third, it is likely that the data contains both single-plant and multi-plant firms. For instance, in Helpman et al. (2004) and Tintelnot (2016) firms optimally trade off the fixed costs associated with duplicating production across multiple plants with the decrease in variable costs arising from either lower transport, trade costs, or different local input prices. Given the CES-demand structure, the presence of multi-plant production does not affect the set of available firms or varieties. Also, if variable cross-border trade costs were zero, two regions at either side of the border would be supplied from the same plant. In this case, we would observe no price differences. If, however, we observe price differences at the border, it must mean that there are variable cross-border trade costs that keep certain firms from doing so.[23]

At the same time, two assumptions are indispensable to detect the presence of positive fixed cross-border trade costs through the two testable conditions of Proposition 1. The framework does not encompass models with non-CES preferences as in Melitz & Ottaviano (2008), Fajgelbaum &

[23] In this case, price differences would reflect both the variable trade cost and the price difference that reflects a deviation from producing at the most efficient plant.

Khandelwal (2016) and Arkolakis et al. (2019), or with non-constant marginal costs like Almunia et al. (2021). Without these assumptions, sufficiently large cross-country taste variation could in principle generate differences in prices and product availability even if trade frictions are zero.

5 Estimating regional cost-of-living differences

In this section, we estimate regional cost-of-living differences between all EU and US region pairs, per category and year. Equation 5 highlights that taste and product availability differences depend on the variety- and firm-level elasticities of substitution. Therefore, we first estimate the variety-level elasticities of substitution. We then use these estimates to construct firm-level price and quantity indices and obtain the firm-level elasticities of substitution. Finally, by decomposing the variance of cost-of-living differences into taste, price and product availability differences, we provide a first insight into the magnitude and sources of regional cost-of-living differences.

5.1 Variety-level elasticities - σ_p

Estimation strategy Applying Shephard's lemma to the firm-level unit expenditure function in Equation 3, demand for variety i in region l at time t is given by:

$$C_{pfi,lt} = \xi_{pfi,lt}^{\sigma_p - 1} \left(\frac{P_{pfi,lt}}{P_{pf,lt}} \right)^{-\sigma_p} C_{pf,lt}$$

Taking logs, we have:

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

where small letters indicate logarithmic transformations of level variables. In addition to recording the location of consumption, the transaction data also registers in which retail chain c the transaction took place. To estimate elasticities of substitution, we, therefore, consider the following empirical demand model at the variety-retail chain-region level:

$$c_{pfic,lt} = -\sigma_p p_{pfic,lt} + \theta_{pfic,n(l)y(t)} + \theta_{pfic,n(l)w(t)} + \lambda_{pfc,lt} + \varepsilon_{pfic,lt} \tag{6}$$

where $\varepsilon_{pfic,lt}$ subsumes the structural residual $\xi_{pfi,lt}$. Two sources of endogeneity complicate estimating the elasticity of substitution σ_p. First, the price and consumption index $P_{fp,lt}$ and $C_{fp,lt}$ are a function of the demand shock $\xi_{pfi,lt}$ which simultaneously determines the quantity level. To overcome this challenge, we include $\lambda_{pfc,lt}$ which absorbs all index-level variation.[24] Second, because prices are likely chosen with prior knowledge of $\xi_{pfi,lt}$, they may be correlated with $\xi_{pfi,lt}$. To deal with this second concern, we capitalize on the fact that we also observe consumption at the

[24]Including index-level fixed effects is a common strategy to deal with these unobservables, e.g. Atkin et al. (2018), Arkolakis et al. (2019) and Faber & Fally (2021).

retail chain level. In particular, Dellavigna & Gentzkow (2019) show that retail chains tend to follow uniform pricing strategies: while they frequently change prices over time, for instance through temporary discounts, they limit spatial variation to a minimum. Once we condition on the seasonal variation in prices and quantities, the lower-frequency variation in these variables should reflect variation due to cost factors. To control for such seasonal variation, first note that the fixed effects $\lambda_{pfc,lt}$ do not only control for the price and quantity indices but also for time-varying demand shocks that affect the varieties supplied by a specific firm in a given location in a given chain similarly. We also include $\theta_{icn(l),y(t)}$, i.e. variety-chain-country-year fixed effects, and $\theta_{icn(l),w(t)}$, i.e. variety-chain-country-week of year fixed effects to control for seasonal variation at the variety-retail chain level. These fixed effects filter out variety-retail chain level seasonality at the weekly level and allow the seasonal patterns to change from year to year. As a final measure to deal with price endogeneity, we construct a Hausman (1996)-type instrument following Dellavigna & Gentzkow (2019). In particular, for each variety-retail chain-week observation, we instrument the price with the average price of the same variety in other regions of the same country. This relies on the assumption that, conditional on the included fixed effects, local demand shocks are not correlated across regions.

Baseline results To estimate category-varying elasticities of substitution, we estimate Equation 6 for each product category separately. We restrict the sample to variety-retail chain combinations with positive sales in at least 50% of the weeks in a given year; see Appendix D for further discussion. Table D.1 and Figure D.1 present the baseline OLS and IV estimates. All OLS estimates have a negative sign but also represent quite inelastic residual demand curves, with elasticities of -1.96 and -0.22 for the 10^{th} and 90^{th} percentiles of the distribution across categories. The IV estimates are generally precise and larger than the OLS estimates in absolute value.[25] The median elasticity is -2.77, and the 10^{th} and 90^{th} percentiles of the distribution are -4.77 and -1.15 respectively. In addition, we reject the null hypothesis that the elasticities are equal to -1 for all but two categories.[26] While Hottman et al. (2016) report somewhat more elastic variety-level estimates, the estimated elasticities are quantitatively in line with the estimates reported in different strands of literature. For comparable US scanner data, Dellavigna & Gentzkow (2019), Faber & Fally (2021) and Döpper et al. (2022) report variety-level elasticities between -2.6 and -2, and Fajgelbaum et al. (2020) use -2.53 as the preferred variety-level elasticity using US trade data.

Robustness We consider three different robustness checks. First, when we do not place any restrictions on the sample, Table D.1 shows that the IV estimates are less elastic. For instance, the 10^{th} and 90^{th} percentiles of distribution become -3.45 and 0.52. By placing stricter restrictions on

[25]The precision of the IV-estimates is due to the generally high first-stage F-statistics. The Kleibergen-Paap statistic has an unreported 10%-90% range of $[12.35, 1098.44]$ across categories.

[26]We are unable to estimate elasticities of substitution for the Skincare - Makeup and Infant food categories because they have too few observations, conditional on the fixed effects. Failing to obtain IV-estimates is common (see e.g. Hottman et al. (2016); Jaravel (2019)). If we are unable to estimate the elasticity, we set it equal to the median value of elasticities across product categories when constructing cost-of-living differences.

the sample in terms of the frequency of positive sales and on the minimal required market share, the estimates become more elastic. When we restrict the frequency at 26 weeks and the variety-level market share at 0.1%, the distribution of elasticities is almost identical.

Second, the baseline specification uses data at the weekly frequency. Figure D.2 and Table D.2 shows the results when we estimate the elasticities using a monthly frequency. The IV estimates are almost always precisely estimated but they are also generally less elastic. In addition, Table D.2 indicates that there are slightly more categories with inelastic demand. As the weekly estimates are more robust and will provide more conservative results, given that the estimated elasticities are higher, we use the weekly elasticities as input for the subsequent analyses.

Finally, the theoretical framework does not have a retail chain dimension, so there is some leeway as to how we deal with regional time-varying demand shocks. Table D.1 shows that the results are robust to replacing the firm-chain-category-region-time fixed effects with firm-chain-category-country-time fixed effects. In this case, we recover a more elastic median demand elasticity of -3.89, but the 10^{th} and 90^{th} percentiles of the distribution also become wider and are given by -8.89 and 4.20. When we include only firm-category-region-time fixed effects instead of the firm-chain-category-region-time fixed effects, the median elasticity is estimated at -3.12 and the 10^{th} and 90^{th} percentiles of the distribution are -5.01 and -1.15.

5.2 Firm-level elasticities - η_p

Estimation strategy Applying Shephard's lemma to the category-level unit expenditure function in Equation 3, demand for firm f in region l at time t is given by:

$$C_{pf,lt} = \xi_{pf,lt}^{\eta_p - 1} \left(\frac{P_{pf,lt}}{P_{p,lt}} \right)^{-\eta_p} C_{p,lt}$$

Taking the log transformation of the firm-level residual demand curve yields:

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

and its empirical counterpart is given by:

$$c_{pf,lt} = -\eta_p p_{pf,lt} + \theta_{pf,l} + \lambda_{p,lt} + \varepsilon_{pf,lt} \tag{7}$$

where $\varepsilon_{pf,lt}$ subsumes $\xi_{pf,lt}$. Like before, estimating the elasticities of substitution η_p is complicated by two endogeneity concerns.[27] First, the unobserved demand shifters simultaneously determine the category-level price and quantity indices and the quantity demanded. Like before, we include the category-region-time fixed effects $\lambda_{p,lt}$ which absorbs all variation at the level of price and consumption indices. Second, if firms have prior knowledge of $\xi_{pf,lt}$ and take this information into account

[27] In addition to the endogeneity concerns, we also have to construct the firm-level price and quantity indices. We provide more detail in Appendix D.

when setting prices, firm-level prices will be correlated with the error term. On the one hand, the inclusion of $\lambda_{p,lt}$ already controls for time-varying regional demand shocks that affect all firms similarly in category p in region l. On the other hand, we add θ_{pfl}, which are category-firm-region fixed effects, and which pick up persistent differences in firm-level tastes across regions. Even conditional on the fixed effects, there might still be variation in $\xi_{pf,lt}$ over time that is correlated with firm-level prices. For this reason, we additionally rely on an instrument that follows from the structure of the demand system and the normalization made in Equation 2.[28] Following Hottman et al. (2016), the firm-level price index can be written as a product of three terms (see Appendix D):

$$P_{pf,lt} = \tilde{P}_{pf,lt} \left(\sum_{i \in \Omega_{pf,lt}} \frac{S_{pfi,lt}}{\tilde{S}_{pfi,lt}} \right)^{\frac{1}{1-\sigma_p}} \tilde{\xi}^{-1}_{pf,lt}$$

The first part is the unweighted geometric average across variety-level prices offered by firm f in category p, region l at time t. Clearly, if firms have prior knowledge of $\xi_{pf,lt}$, this first part of the firm-level price index is correlated with $\xi_{pfl,t}$. The second part of this expression depends on the dispersion in variety-level market shares within each category-firm-region-time cell. Intuitively, greater dispersion in taste-adjusted prices induces more dispersion in market shares, leading to a fall in the geometric average of the market shares. Importantly, the relative within category-firm-region-time market shares do not depend on $\xi_{pf,lt}$ as $\xi_{pf,lt}$ affects all varieties within the firm-level nest equally. The final part of this decomposition is the unweighted geometric average of variety-level taste shifters. Given the normalization made in Equation 2, this part is time-invariant and will be partialled out with the inclusion of $\theta_{pf,l}$. The second part of this decomposition co-determines firm-level prices and is uncorrelated with the firm-level taste parameter, making it a suitable instrument.[29]

Baseline results We estimate category-specific elasticities of substitution by estimating Equation (7) separately for each category. We include all varieties that register positive sales more than 50% of the time in a given year. Figure D.3 shows the baseline results. The OLS estimates are all negative, precisely estimated but relatively inelastic as they almost always fall within a range from -2 to -1.

[28] There is a conceptual and a practical reason why we do not rely on the Hausman-type instrument at the firm level. Conceptually, section 4 does not explicitly model consumer preferences for different retail chains. When estimating the elasticities of substitution at the variety level, we interacted the fixed effects with the retail chain dimension and allowed for different consumer preferences across different retail chains without taking a stance where preferences for retail chains would enter the preference system. However, at the firm level, the price and quantity variables already represent aggregated variables. Hence, if we had taken the same approach we would have implicitly assumed that preferences for retail chains enter as an additional nest on top of the firm- and variety-level nests. Therefore, applying the same approach would require additional assumptions on the preference system. When we disregarded these conceptual objections and implemented the same approach, the power of the Hausman instrument at the firm level was low. Therefore, from a practical point of view, the same approach would not be a suitable strategy at the firm level.

[29] This strength of the instrument relies on the presence of multi-product firms and imperfect substitutability across varieties which. When only one product is supplied, the dispersion in market share is zero. If varieties are perfect substitutes ($\sigma_p \to \infty$), market shares are disconnected from taste-adjusted prices leading to no dispersion in market shares.

We turn to the IV estimates next. First, the instruments are strong as the first-stage F-statistics are almost always larger than the conventional rejection levels for weak instruments.[30] Second, the IV estimates imply more elastic residual demand curves as they are centered around -3.10 and have a 10%-90% range of $[-4.84, -1.71]$.[31] Relative to variety-level estimates, there are comparatively few papers that estimate firm-level elasticities of substitution. Hottman et al. (2016) is one of the few papers that estimate firm-level elasticities and report estimates between $[-7.3, -2.6]$ centered around -3.9. Therefore, our estimates are quite close to theirs, albeit slightly less elastic.

Robustness We consider three robustness checks. First, Table D.3 shows that the elasticities are very similar across different sample restrictions. This is because the data becomes much less sparse when we collapse the retail chain and variety dimensions. Hence, imposing the same sample restrictions does not result in markedly different samples.

Second, similar to the product-variety estimates, the distribution of monthly firm-level elasticities is shifted upwards when we collapse the data at the monthly level. While the elasticities are still precisely estimated, Table D.4 shows that the distribution of monthly estimates is centered around -1.66 and has a compressed range from -3.20 to -1.32.

Third, the baseline estimation includes category-firm-region fixed effects and thus controls only for persistent differences across firms within regions. However, if retail chains and firms coordinate on seasonal price changes and promotion, an alternative identification strategy could be to use time variation conditional on seasonal shocks. For this reason, we re-estimate Equation 7 by replacing the θ_{pfl} fixed effects with category-firm-region-year fixed effects, $\theta_{pfl,y(t)}$, and category-firm-region fixed effects-week-of-the-year $\theta_{pfl,w(t)}$. This set of fixed effects also flexibly controls for seasonal demand shocks that could drive both firm-level demand and prices. Nevertheless, Table D.3 shows that the estimated distribution of elasticities is quantitatively similar to the baseline results.

Implied markups As an additional check we assess what the estimated elasticities of substitution imply for the firm-level markups. Under Bertrand price competition, firm-level markups depend on the firm-level elasticity of substitution and on the firm-level market share in location l at time t. In particular, markups are equal to $P_{il,t}/MC_{il,t} = \left(\eta_p - (\eta_p - 1)\, S_{fpn,t}\right) / \left(\eta_p - (\eta_p - 1)\, S_{fpn,t} - 1\right)$ where $S_{fpn,t}$ is the firm-level market share. Figure D.4 shows the full distribution of recovered firm-level markups across category-firm-country-year observations. We recover a median firm-level markup of 1.5, i.e. the median firm charges a 50% price premium over its marginal costs.

How sensible are these markup estimates? We benchmark our estimates to the broader literature on markup estimation. There are two broad strands in this literature. First, the demand approach estimates markups by specifying a model of demand and competition between firms. Our approach falls in this strand. Other papers that take the demand approach to estimate markups for a broad

[30] More precisely, the first-stage Kleibergen-Paap F-statistics have a 10%-90% range of $[15.60; 5,830.67]$ while the smallest F-statistic is 7.24.

[31] The estimation routine successfully completes for all categories and we reject the null hypothesis that the elasticities are equal to -1 for all the categories.

set of categories are Hottman et al. (2016) and Döpper et al. (2022). While Hottman et al. (2016) find a median markup of 1.31, Döpper et al. (2022) report a median markup of 2.08.[32] Second, the production approach, pioneered by De Loecker & Warzynski (2012), obtains markups by estimating a production function in combination with an assumption of cost minimization with respect to a variable input. De Loecker et al. (2016) and De Loecker et al. (2020) report a median elasticity of 1.6 for Indian manufacturing firms and an average markup of 1.6 for public US companies. Our estimates are therefore broadly in line with both strands in the literature.

5.3 Regional cost-of-living differences

Following Equation 5, we compute differences in taste ($T^{kl}_{p,t}$), prices ($L^{kl}_{p,t}$) and product availability ($\Lambda^{kl}_{p,t}$) for each region pair (k, l) per category p and year t, and we construct cost-of-living differences ($P^{kl}_{p,t}$) as the sum of these three terms. Table 2 presents a set of moments of the conditional distributions of regional cost-of-living differences and a variance decomposition into the three components. To account for sampling uncertainty and estimation uncertainty, we compute these moments for 50 bootstrap samples. We show the average and 95% percent confidence intervals across bootstrap samples.[33]

The first three columns of Table 2 show the 10^{th}, 50^{th} and 90^{th} quantiles of the distribution of cost-of-living differences across product categories and years for international and domestic regions, separately for the EU and the US. The 50^{th} percentile, Q_{50}, illustrates that the conditional distributions of cost-of-living differences are more or less centered around zero for both the EU and the US. As mentioned before, the lack of information on production locations implies that the sign of cost-of-living differences is not determined. Nonetheless, Proposition 1 shows that differences in the dispersion in cost-of-living differences between and within can be leveraged to provide more insights into cross-border market segmentation. Indeed, the 10^{th} and 90^{th} percentiles, Q_{10} and Q_{90} respectively, show that while cost-of-living differences are comparable between and within US states, they appear much larger between than within EU countries.

The next three columns provide more insights into the sources of these regional cost-of-living differences by decomposing the variance of $P^{kl}_{p,t}$ into taste, price and product availability differences. First, whereas most of the literature dealing with within-country differences in cost-of-living differences has focused on LOP deviations and product availability between regions of the same country, e.g. Handbury & Weinstein (2015) and Feenstra et al. (2020), differences in consumer taste turn out to be the most important factor explaining cost-of-living differences within and between countries. This underscores the quantitative importance of controlling for taste differences when assessing the presence of geographic market segmentation. Second, differences in consumer taste

[32]These papers report different measures of the markup. Hottman et al. (2016) report a median $\frac{P-MC}{MC}$ of 0.31, which results in a median $\frac{P}{MC}$ of 1.31. Döpper et al. (2022) report a median Lerner index $\frac{P-MC}{P}$ of 0.48 which results in a median $\frac{P}{MC}$ of 2.08.

[33]In each region and in each year, we sample households with replacement and weigh each household with the provided population weights.

are roughly equally important in explaining cost-of-living differences between US states as they are within US states (accounting for respectively 85% and 83% of the variance). This is also true for price and product availability differences, which collectively make up less than 20% of the variation in cost-of-living differences between and within US states.[34] Consistent with the reduced-form evidence, the situation is different for European region pairs. The joint importance of LOP deviations and product availability differences is a little over 13% for domestic region pairs (similar to the US), and it rises to more than 40% for international European region pairs. Finally, the variation in LOP deviations is quantitatively much smaller than the variation in product availability differences. This is true both between and within countries. We stress that the relative importance of price and product availability could not be assessed from the reduced-form evidence alone.

Table 2: 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	$.148$
	$[-.36,-.333]$	$[.135,.146]$	$[.741,.853]$	$[.79,.879]$	$[0,0]$	$[.121,.21]$
$\mathbb{1}\left(B^{kl}=1\right)$	$-.638$	$.02$	$.728$	$.826$	$-.001$	$.175$
	$[-.675,-.609]$	$[.019,.021]$	$[.693,.773]$	$[.781,.843]$	$[-.002,0]$	$[.158,.22]$

Notes: The first three columns show the 10^{th}, 50^{th} and 90^{th} quantiles of the distribution of cost-of-living differences across product categories and year for international and domestic EU and US regions separately. The last three columns show a variance decomposition of cost-of-living differences into in taste ($T^{kl}_{p,t}$), prices ($L^{kl}_{p,t}$) and product availability ($\Lambda^{kl}_{p,t}$). We compute the set of moments in three steps. First, we construct 50 bootstrap samples of households in each region by redrawing households with replacement, based on the population weights. Second, for each bootstrap sample, we draw elasticities of substitution from their empirical distribution and construct cost-of-living differences between region pairs kl and three components following Equation 5. Finally, for the quantiles of the distributions of cost-of-living differences, we present the average of each of the moments and the 95% confidence interval across the 50 bootstrap samples. To compute the variance decomposition, we rely on the properties of OLS and regress each of the components on total cost-of-living differences. This approach allocates the covariance terms equally between the components. We present the average of each of the moments and the 95% confidence interval across the 50 bootstrap samples.

6 Cross-border market segmentation in the EU and the USA

We now implement the spatial differencing strategy described in Proposition 1. First, we apply the strategy to overall cost-of-living differences to establish an upper bound on the effect of geographic

[34]The negatively estimated contribution of price differences is due to a small variance component and negative co-variance terms.

market segmentation on cost-of-living differences. Second, we apply the strategy separately to taste differences, LOP deviations, and differences in product availability to investigate the sources of geographic market segmentation.

6.1 Implementing Proposition 1

Proposition 1 has to be operationalized in two respects. First, it is expressed in terms of two potential outcomes (international and domestic region pairs) and in the data we observe only one of these. We will rely on a conditional independence assumption to construct the missing counterfactual. Second, Proposition 1 compares regions with equal geographic characteristics and in the data we only have a finite number of regions. We will therefore instead compare regions that are sufficiently close.

Conditional independence To construct the missing counterfactual (domestic region pair for an international pair), we assume that the separation of two geographically similar regions by a border was not shaped by the cost of living differences observed today. Under this assumption, we can construct the counterfactual cost-of-living differences for international region pairs by relying on observed cost-of-living differences for domestic region pairs.

More formally, we make the following conditional independence assumption:

$$B^{kl} \perp\!\!\!\perp \left(P^{kl}_{p,t}(1), P^{kl}_{p,t}(0) \middle| \boldsymbol{X}^{kl} = 0\right)$$

where we previously defined $P^{kl}_{p,t}(1), P^{kl}_{p,t}(0)$ as the potential cost-of-living differences if (k, l) is an international or a domestic region pair. As cost-of-living differences are constructed from taste, price and product availability differences, we assume that the conditional independence assumption equally holds for the individual components.

We consider this assumption to be plausible for two reasons. First, there is evidence that geographic differences determine border assignment. For instance, Nunn & Puga (2012) show how mountainous areas and rivers shielded nations from invasions and Alesina & Spolaore (1997) illustrate how more distant and larger populations are more difficult to govern. At the same time, geographic differences also determine transport costs, which feed into the potential cost-of-living differences. However, by conditioning on geographic characteristics, we eliminate this source of confounded assignment. Second, European country borders and US state borders have been stable in recent times. It is therefore unlikely that that the historic border assignment was made with today's potential cost-of-living differences in mind.[35]

[35] In addition to the conditional independence assumption, we also require individualistic and probabilistic assignment. Individualistic assignment requires that separating a region pair by a national border does not affect the potential outcomes of other region pairs. For instance, there are 3,403 region pairs in Europe. If we were to allocate a Belgian region to the Netherlands, there would be 9 additional borders with Belgium and 12 fewer borders with the Netherlands which amounts to a 1% change in the number of units. While not zero, this number seems small enough to assume that the change in the economic environment that determines the potential outcomes is negligible. Probabilistic assignment requires that every region pair needs to have a probability of being separated by a border strictly different from zero and one. In the data, both contiguous and very geographically distant international and domestic region pairs co-exist.

One possible concern is that price and product availability differences might induce households to engage in cross-border shopping. This could potentially undermine border compliance between European countries, where price and product availability differences are especially large. To understand the importance of this source of non-compliance, we use the Belgian data for which the variable containing the store name indicates whether the store is located in Belgium or in one of the neighboring countries.[36] While there is some cross-border shopping, Table E.1 and Figure E.1 show that over 97% of expenditure by Belgian households is made in stores located in Belgium. Moreover, the overall expenditure share on cross-border transactions in very close proximity to the border remains low at a little over 5% and 10% for the French and Dutch borders respectively.

A matching estimator Under the conditional independence assumption, we construct counterfactual cost-of-living differences for international region pairs using cost-of-living between domestic region pairs. While this conditional expectation is a strict equality, in practice, we have only a finite number of regions and we are only able to find regions k and l that approximately satisfy this condition. We therefore implement the conditional expectation in Proposition 1 as follows:

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

where $\mathcal{D}_\varepsilon \equiv \{(k,l) : B^{kl} = 1 \cap F\left(D\left(\boldsymbol{X}^{kl}\right)\right) \leq \varepsilon\}$ is the set of international region pairs $\left(B^{kl} = 1\right)$ for which the Mahalanobis distance in terms of geographic characteristics $D\left(\boldsymbol{X}^{kl}\right)$ is below ε^{th} percentile of the distribution of Mahalanobis distances across all region pairs, $F(\cdot)$.[37] This matching estimator embodies two steps. First, we restrict attention to international region pairs that are geographically sufficiently close $\left(F\left(D\left(\boldsymbol{X}^{kl}\right)\right) \leq \varepsilon\right)$. Second, for each international region pair $(k,l) \in \mathcal{D}_\varepsilon$, we construct its counterfactual, e.g. $\hat{L}^{kl}_{p,t}(0)$, as an average over the set of domestic region pairs to which either k or l belongs and for which it also holds that $(k,l) \in \mathcal{D}_\varepsilon$.

6.2 Detecting cross-border market segmentation

This section provides the main results of this paper. We apply the matching estimator to cost-of-living $(P^{kl}_{p,t})$, taste $(T^{kl}_{p,t})$, price $(L^{kl}_{p,t})$ and product availability differences $(\Lambda^{kl}_{p,t})$. In the baseline results, we compute the estimates by restricting the set of admissible international region pairs at a cut-off value of $\varepsilon = 0.1$. For each international pair, we compute the counterfactual by choosing the domestic region pair that has the smallest geographic distance from either l or k. Below, we discuss the robustness of the results when we consider different implementations of the matching estimation in which we vary ε and the number of domestic region pairs to construct the counterfactual.

[36] As Belgium tends to have higher consumer prices for the products we study (e.g. Beck et al. (2020)) and is well-connected to its neighboring countries, cross-border shopping would manifest itself, especially in Belgium.

[37] As geographic characteristics, we include the longitude and latitude of each region's population-weighted centroid, the remoteness of the region and the ruggedness (see Nunn & Puga (2012)).

Baseline results Table 3 presents the estimated differences in the absolute value of cost-of-living, taste, price and product availability differences between international and matched domestic region pairs, separately for Europe and the USA.[38] Below the estimated differences, we present block-bootstrapped 5%-95% confidence intervals computed from 50 iterations.[39] As a benchmark, we also show the average absolute cost-of-living, taste, price and product availability difference for the set of matched domestic region pairs.

Panel (a) of Table 3 shows the results for EU regions. First, column (1) shows that absolute cost-of-living differences are significantly larger between countries than within them. This difference is also economically important: absolute cost-of-living differences are on average 37.9 percentage points larger for international than domestic region pairs, or 2.5 times larger in relative terms (i.e. $(0.3787 + 0.26)/0.26 \approx 2.5$).

Second, column (2) shows that taste differences are significantly larger between than within countries as well. Hence, taste differences are not only key to explaining within-country cost-of-living differences (see Table 2), but they are also considerably higher between European countries. In fact, absolute differences in consumer taste are 30.4 percentage points or about 2.3 times larger between than within European countries (i.e. $(0.3041 + 0.2372)/0.2372 \approx 2.3$).The finding that taste differences are much larger between than within countries provides a cautionary warning to literature that quantifies geographic market segmentation based on cross-sectional variation in trade shares. Without controlling for taste variation, this approach likely over-predicts the effect of cross-border trade frictions on outcomes of interest.

Third, columns (3) and (4) indicate that price and especially product availability differences are also considerably larger between than within EU countries, by on average respectively almost 10 and 30 percentage points. Following Proposition 1, these findings have two implications. First, there exist considerable variable and fixed trade frictions between EU countries. In other words, consumer markets for grocery products across EU countries remain subject to substantial cross-border market segmentation. Second, while the literature has predominantly focused on price differences as a manifestation of cross-border market segmentation, differences in product availability are three times more important. Put differently, our results suggest that fixed trade frictions are a much more important source of cross-border market segmentation than variable trade costs.

Panel (b) of Table 3 presents the results for US regions. Although cost-of-living, taste, price and product availability differences are statistically larger between than within US states, the differences are quantitatively small. For instance, whereas cost-of-living and taste differences are respectively 37.9 and 30 percentage points larger between than within EU countries, they are less than one percentage point larger between than within US states. Equally important, we also find that the small price and product availability differences within US states are quantitatively very similar to those within EU countries.

[38]Note that because we consider differences in absolute differences, the individual effects (taste, price and product availability) do not exactly sum to the effect for total cost-of-living differences.

[39]These block-bootstrapped standard errors account for sampling uncertainty due to a limited sample of households and for estimation uncertainty regarding the elasticities of substitution.

In sum, the US shows considerable market integration both within and between states. The EU also shows considerable market integration within countries, but strong cross-border segmentation between countries.

Table 3: Geographic market segmentation: Estimation results

Y	$P_{p,t}^{kl}$	$T_{p,t}^{kl}$	$L_{p,t}^{kl}$	$\Lambda_{p,t}^{kl}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.3787***	.3041***	.0967***	.2972***
	[.3548, .4114]	[.2866, .3276]	[.0953, .0977]	[.2768, .3259]
$\mathbb{E}\left[\hat{Y}_{p,t}^{kl}(0)\right]$	.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]
$\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}(0)\right]$	.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: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $10\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from one matched domestic region pair. Column (1) shows the results for cost-of-living differences $\left(P_{p,t}^{kl}\right)$, column (2) for taste differences $\left(T_{p,t}^{kl}\right)$, column (3) for price differences $\left(L_{p,t}^{kl}\right)$ and column (4) for product availability differences $\left(\Lambda_{p,t}^{kl}\right)$. We show the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Placebo estimates To strengthen the claim that the differences in price and product availability differences are much more important between EU countries relative to between US states, we consider a falsification test. In particular, we compare the average treatment for price and product availability differences that underlie columns (3) and (4) of Table 3 to a distribution of placebo estimates.[40] If there is truly a treatment effect that drives the results documented in Table 3, they should be statistically different from the distribution of placebo estimates. More specifically, we compute the distributions of placebo estimates as the difference in the price and product availability differences between a domestic region pair, now counterfactually considered to be an international pair, and other domestic region pairs that act as matched control region pairs.

Figures 4a and 4b compare the distribution of treatment effects for absolute price differences to the distribution of placebo estimates, separately for EU and US regions. Figure 4a shows that for EU regions the average treatment is outside of the range spanning the 5^{th} and 95^{th} percentiles of the distribution of placebo estimates. Based on Proposition 1, this confirms the presence of cross-border variable trade frictions. In contrast, Figure 4b shows that for US regions we cannot reject the null hypothesis that the small but positive treatment effect between US regions could have been drawn from the distribution of placebo estimates. Therefore, we cannot reject the null hypothesis of zero cross-border variable trade frictions between US states.

Figures 4c and 4d repeat the same falsification tests for differences in absolute product availability differences for EU and US region pairs. As with price differences, for EU regions the average treatment is well outside the 5^{th} and 95^{th} percentiles of the distribution of placebo estimates. It is therefore likely that the average differences in absolute product availability differences between EU countries reflect the presence of positive cross-border fixed trade frictions. As with price differences, this is again not the case for US regions. We find that the average treatment effect for product availability between US states is firmly within the range spanning the 5^{th} and 95^{th} percentiles of the distribution of placebo estimates. Hence, we cannot reject the null hypothesis of zero cross-border fixed frictions between US states.

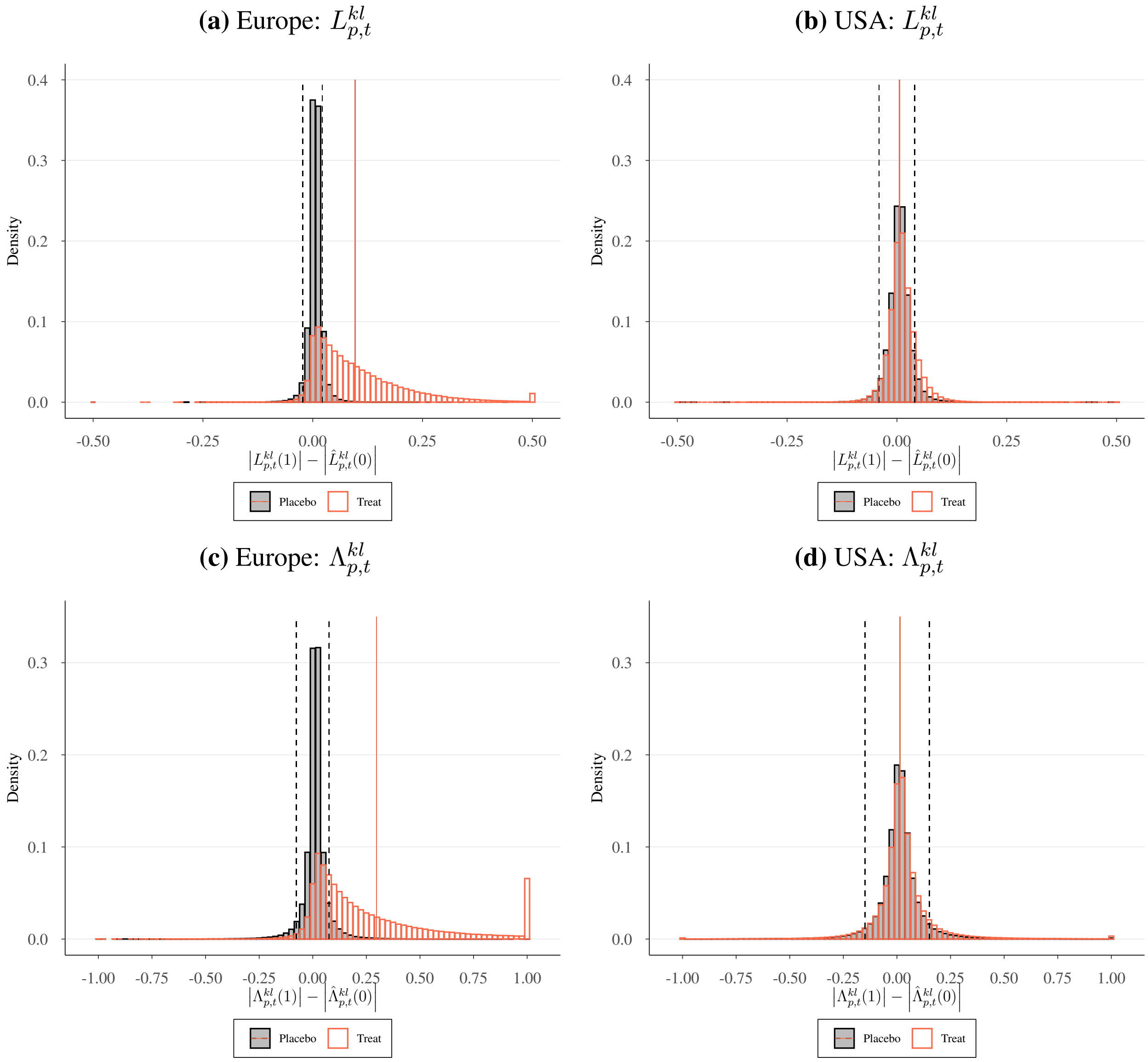
Different matches The baseline results implemented the matching estimator by restricting the set of admissible international region pairs to the pairs with a geographic distance below the 10^{th} percentile of the empirical distribution of geographic distances and by matching computing the counterfactual outcomes from one matched domestic region pair. First, Tables E.2 - E.3 show that the baseline results are largely unaltered when we instead compute the counterfactuals based on the two or three domestic region pairs with the smallest geographic distance from either l or k. Hence, our results are not sensitive to the number of control units used to construct the counterfactuals. Second, Tables E.4 - E.12 show that the results are also quantitatively very close to the baseline results when we consider different cut-off values to determine the set of admissible region pairs.[41]

Markups The baseline results for price differences are obtained under the assumption of constant markups. If markups instead depend on the local market environment, they might differ between regions. In the literature on geographic market segmentation, there are two views on whether markups should be included in the quantification of geographic market segmentation. On the one

[40]The individual treatment effects vary at the region pair, product category and year level.

[41]We consider the following range of cut-offs: $\varepsilon = \{0.2, 0.15, 0.1, 0.5\}$.

Figure 4: Placebo estimates



Notes: This figure compares the distributions of treatment effects to the distribution of placebo estimates for absolute price and product availability differences. Figure 4a plots the distribution of individual treatment effects for absolute price effects, $\hat{\tau}^{kl}_{p,t,L,\varepsilon}$, between EU regions in red and the distribution of placebo effects between EU regions for absolute price effects in grey. We indicate the average effect effect with a vertical solid line. We also indicate the 5^{th} and the 95^{th} percentiles of the distribution of placebo estimates with dashed grey lines. Figure 4b shows the same distributions between for US regions. Figures 4c and 4d show the results of the same exercise for absolute differences in product availability differences, $\hat{\tau}^{kl}_{p,t,\Lambda,\varepsilon}$ for EU and US regions respectively. The distributions of treatment effects are based on the individual treatment effects, which vary at the region pair, product category and year, that underlie Table 3. The placebo distributions are computed in a similar way but differ in that treated units are not international region pairs but domestic region pairs.

hand, there is a literature that approaches the problem of geographic market segmentation from the point of consumers and that considers LOP deviations at the border as reflecting transaction costs (e.g. Gopinath et al. (2011); Beck et al. (2020); Duch-Brown et al. (2021)). In this case, markups should be part of the computation and this is the view reflected in Table 3. On the other hand, there is a literature that interprets geographic market segmentation as stemming from trade frictions faced by producers (e.g. Atkeson & Burstein (2008); Head & Mayer (2021)). In this case, geographic market segmentation stems from variation in the marginal costs of serving different markets. To this end, we distinguish between marginal costs and markups by computing markups by following Atkeson & Burstein (2008); Edmond et al. (2015); Crowley et al. (2023) and assuming that in each market firms set prices in an oligopolistic market environment. In this case, firms will adjust their markups across markets depending on their relative size in the respective markets.[42] Tables E.13-E.15 show the results when we apply the matching estimator to cost-of-living differences and each of its components for a distance cut-off value of 10% and for one, two and three matched domestic region pairs as control units respectively.[43] We find that both marginal cost and markup differences are significantly higher between than within countries. However, cost differences are more than eight times more important compared to markup differences between EU countries and US states. In line with price differences, marginal cost differences are much more important between EU countries compared to US states. This implies that under the assumptions on market structure, most of the price differences stem from cost differences and that focusing on price differences reflects the type of market segmentation that both strands of the literature consider.

CES versus Nested CES Section 4 shows that the assumption on preferences dictates how cost-of-living differences and each of its components are computed. Throughout the analysis, we have assumed that preferences follow a nested CES demand system with the upper nest at the firm level and the lower nest at the variety level. However, this likely affects the quantitative magnitude of taste, price and product availability differences. A natural question is how the results would be affected if we were to change the assumption of consumer preferences from a nested CES to a regular CES preference system.[44] Tables E.16 - E.18 show the results when we compute and decompose cost-of-living differences under the assumption of regular CES preferences for a distance cut-off value of 10% and for one, two and three matched domestic region pairs as control units respectively. These tables show that the main conclusions are robust to this change in the assumption on consumer preferences. If anything, differences in price and product availability differences between EU countries are now even more pronounced relative to within-country differences, and differences in price and product availability differences between US regions remain equally small. This underscores the importance

[42] Doing so, we assume that retailers are perfectly competitive and distribution costs are part of the marginal cost term. The computed markups are the same as the ones discussed in section 5.

[43] The results for overall cost-of-living differences, taste differences and product availability differences remain unaltered when we split we split price differences into cost and markup differences.

[44] We stay within the class of CES preference system as this allows us to rely on the estimated elasticities of substitution at the variety level.

of incorporating an upper firm-level nest to avoid upward biases from from a simple CES.

7 Conclusion

Assessing the extent of cross-border geographic market integration has been a question of central importance to both researchers and policymakers. Recent studies have reiterated the continued existence of large price differences and differences in trade shares across regions belonging to different European countries relative to regions part of the same country. However, solely focusing on LOP deviations ignores the presence of large differences in product availability, and relying on regional variation in trade shares risks convoluting taste differences with geographic market segmentation.

This paper builds on household-level scanner data with highly detailed data on prices and consumption and develops a test to detect cross-border market segmentation without observing shipment routes, valid in a wide set of international trade models. Cost-of-living differences provide a framework to measure LOP deviations and product availability differences in a common unit, and filter out taste differences. To detect geographic market segmentation without knowledge of transportation routes, we develop a spatial differencing strategy that adjusts between-country variation by within-country variation: the residual variation in LOP deviations and differences in product availability can be attributed to positive variable and fixed trade frictions.

We find that cost-of-living differences are much larger between EU countries than within EU countries. However, the largest share of cost-of-living differences can be attributed to differences in consumer taste. Hence, even in the absence of geographic market segmentation, large cost-of-living differences across European countries will likely remain. At the same time, we find that price and product availability differences are substantially higher between than within EU countries, which demonstrates the importance of cross-border market segmentation in the EU. In stark contrast, we fail to reject to the null hypothesis of zero differences between and within US states. While LOP deviations contribute to the cross-border cost-of-living differences in the EU, differences in product availability are three times more important. This suggests that cross-border fixed trade frictions are more important than variable trade frictions in explaining geographic market segmentation in the EU.

Our data do not allow us to dig deeper into the more fundamental institutional and technological reasons behind these large and persistent differences in prices and product availability. Nevertheless, our analysis does suggest that to reduce geographic market segmentation, stimulating cross-country entry of firms and varieties should be prioritized over focusing on price convergence. We leave it to further research to identify the policies and institutional details that will help the European Single Market achieve its ultimate goal.

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Uncovering the Sources of Cross-border Market Segmentation: Evidence from the EU and the US

ONLINE APPENDIX

A Data Appendix

A.1 Product categories

In each country, barcodes are allocated to different product categories. However, those product categories slightly differ across countries. To consolidate product categories across countries, we create correspondence tables between the country-level product categories and the NielsenIQ product groups. In case a barcode does not belong to the same product category in all countries, we re-assign that barcode to the product category to which the barcode is assigned most frequently in the other countries. This is only necessary for a handful of barcodes. This process yields the 68 product categories used in the analysis.

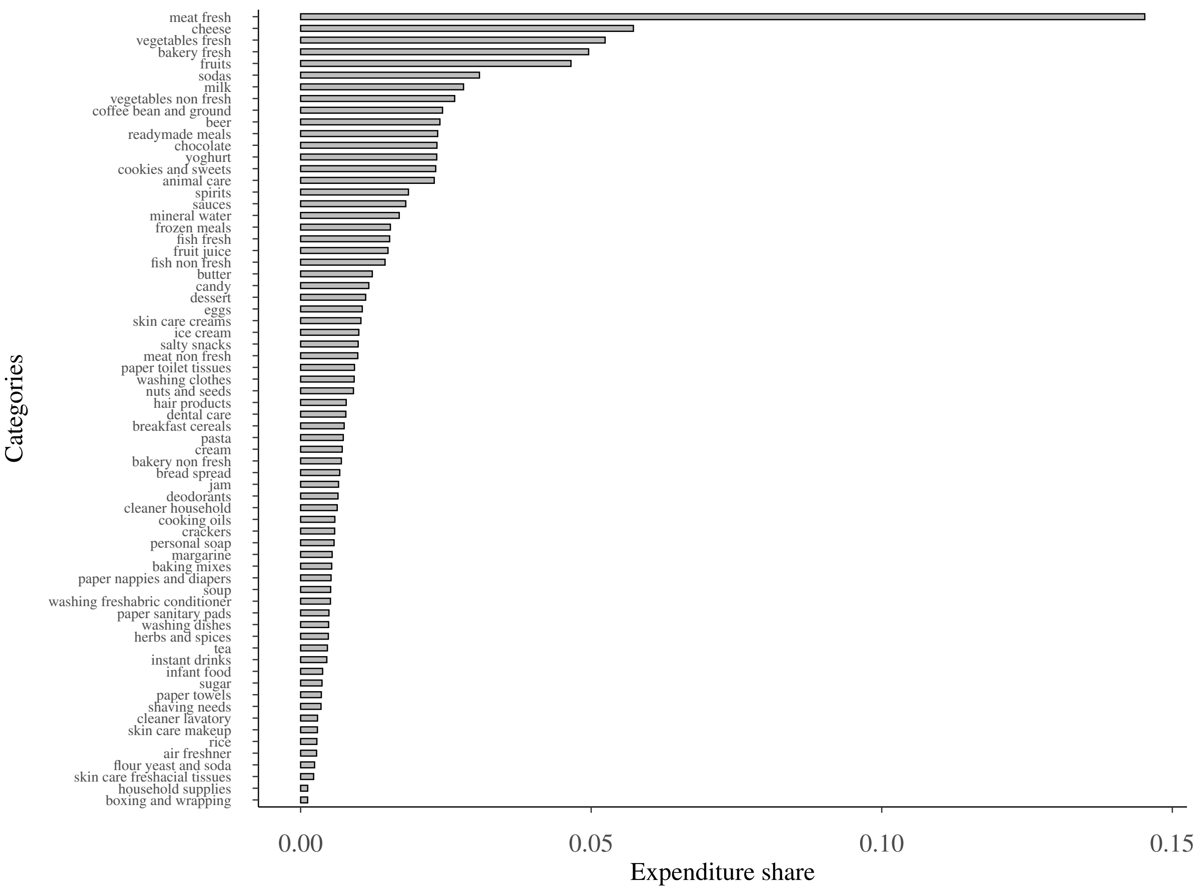
A.2 Categories

Table A.1: Excluded categories

Category	Belgium	France	Germany	Netherlands	Reason
batteries	X	X	X	X	Too few observations
clothing items	X	X	X	X	Too few observations
dietary supplements	X	X	X	X	Too few observations
first aid	X	X	X	X	Reporting issue
flowers	X	X	X	X	Too few observations
insecticides	X	X	X	X	Too few observations
leisure items	X	X	X	X	Too few observations
lighting	X	-	X	-	Not observed
magazines	-	-	X	-	Not observed
medicines	X	X	X	X	Reporting issue
other	X	X	X	X	Too few observations
tobacco	X	-	X	X	Not observed
vitamins	X	X	X	X	Too few observations
wine	X	X	X	X	Reporting issue

Notes: This table provides an overview of the categories that were excluded from the sample. An "X" indicates that the category was present, but was omitted; an "-" indicates that the category was not present. Observations are excluded because they were not present in each country ("not observed"), because the category was observed, but only consumed by less than 5% of the households in the sample ("too few observations") or because there are concerns about how the category is represented. Wine is excluded because France collects a separate household panel for this specific category. First aid and medicines are excluded because countries differ in the extent to which households can access them through regular retail stores. The other category is removed as we are uncertain about the exact nature of such varieties.

Figure A.1: categories



Notes: The graph plots the average expenditure share across the categories. We compute this by pooling expenditure across the countries for each year and then averaging over years.

A.3 Barcodes and Firms

We elaborate on the procedure that we use to associate barcodes with firm ids. The starting point is the data obtained from GS1 that matches the GS1 firm ID to each 8-digit or 13-digit barcode. Then, we assume that with a country, there will be only one firm that owns a particular brand, e.g. Coca-Cola European Partners in Belgium. We do allow for brands to be owned by different firms in different countries. For instance, the soda brand Dr. Pepper is owned by PepsiCo, inc. in most countries, but is owned by Coca-Cola European Partners in the Netherlands. By grouping barcodes through brand-country combinations, we can allow for such structures. As firms may own many country-brand combinations under multiple GS1 firm IDs, we obtain links across GS1 firm IDs when they both own a significant share of barcodes within the same country-brand combination. However, there are a couple of issues with this raw dataset that we need to deal with:

- Even though each barcode is associated with only one GS1 firm ID, within a country-brand combination it is often the case that more than one GS1 firm ID owns barcodes.

- Often retailers are owners of some barcodes within country-(non-private) brand combination, for instance for repacking purposes, we might be grouping white label products with branded products through this feature of the data. An even bigger problem arises when retailers own barcodes across many countries-brand combinations because then we would counterfactually group barcodes that are owned by different firms.

To guard against these concerns, we clean the GS1 firm IDs in the following way.

- We identify all GS1 firm IDs used by retailers for their private labels and remove them from branded barcodes. In this way, we break spurious GS1 firm ID links through IDs associated with retailers.
- We remove all GS1 firm IDs that have a transaction share below 10%. The idea behind this step is to limit the potential for spurious linkages across firms through barcodes that have very little sales. Conversely, if it is really true that a firm has significant operations through more than one GS1 firm ID, it must be that these firm IDs account for a significant transaction share. We note that in most cases there is only one GS1 firm ID that passes this cleaning step, but for some multinationals, e.g. Pepisco, Inc., P&G, it turns out that barcodes in one country are owned by local affiliates of different nationalities of the same multinational.
- Related to the previous point, in cases where the largest GS1 firm ID has a bigger than 80% transaction share in a country-brand combination, we identify this as the only firm ID and remove the smaller ones.
- Finally, we keep only multiple GS1 firm IDs within the same country-brand combination that has a number of transactions that exceeds 200. If the country-brand combination has a transaction count below 200, we only keep the largest GS1 firm ID. In this way, we determine links across GS1 firm IDs using country-brand combinations that are not occasionally offered.

Table A.2: Barcode types

	Nr. barcodes				Expenditure share			
Barcode type	BEL	FRA	GER	NLD	BEL	FRA	GER	NLD
Branded	286,997	266,830	356,698	256,330	0.37	0.59	0.41	0.36
Private label	152,164	128,261	166,571	155,023	0.32	0.35	0.29	0.41
Loose item	42,695	148,048	144,862	46,719	0.23	0.05	0.26	0.12
Excluded	46,408	16,981	60,536	413,991	0.08	0.01	0.04	0.11

Notes: This table provides a sense of the importance of the different barcode types present in the data. Branded products are products that are associated with a non-retailer brand. Private label products are products whose brand coincides with a retail chain. Loose items are unbranded items. The excluded categories contain all expenditure on barcodes that could be classified in a category and which is therefore omitted from the analysis. Columns 2 to 5 and columns 6 to 9 present across countries the importance of each category in terms of the number of barcodes and in terms of the total expenditure respectively.

Table A.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

Notes: This table provides across countries the distribution of the (1) number of firms, (2) firms sales, (3) log of firm sales, (4) numbers of UPCs per firm and (5) sales per UPC. We compute the mean across category-year combinations where we weight category-year observations with category-year expenditures.

Table A.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

Notes: This table provides across countries the mean (1) market share, (2) mean firm market share, (3) mean number of UPCs per firm and (4) median number of UPCs per firm for each firm size decile for each country separately. We compute the mean across category-year where we weigh category-year observations with category-year expenditures.

Table A.5: Size Distribution by firm rank

	Belgium		France		Germany		Netherlands	
Firm rank	Market share	Nr. UPCs	Market share	Nr. UPCs	Market share	Nr. UPCs	Market share	Nr. UPCs
1	25.57	266.7	21.52	248.4	21.02	365.9	23.75	465.8
2	15.04	194.8	12.59	195.1	12.79	267.2	14.55	283.1
3	11.06	139.7	8.53	152.6	8.88	209.7	10.81	355.2
4	8.16	163.7	6.79	144.8	6.40	168.9	7.96	162.0
5	6.11	148.4	5.41	124.5	5.13	150.1	5.82	227.1
6	4.59	106.8	4.66	122.5	4.13	139.8	4.63	205.6
7	3.49	100.8	3.95	117.4	3.44	110.6	3.76	198.7
8	2.84	76.0	3.44	95.5	2.80	78.2	3.03	91.0
9	2.25	59.5	3.02	85.1	2.42	89.0	2.47	191.7
10	1.86	57.7	2.71	82.1	2.14	94.6	2.04	113.5
Other firms	0.08	5.6	0.19	10.2	0.14	9.1	0.09	6.9

Notes: This table zooms in on the first decile of the previous table. It provides across countries the mean (1) firm market share and (2) number of UPCs per firm for the 10 biggest firms in each category-year combination. The mean is computed across category-year combinations where we weight category-year observations with category-year expenditures.

Table A.6: 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

Notes: This table shows across countries (1) the mean number of firms, (2) the total market share (3) the standard deviation of UPC level sales within firms for different bins based on the number of UPCs per firm. The mean is computed across category-year combinations where we weight category-year observations with category-year expenditures.

A.4 Households

We allocate household expenditure to regions based on information about the ZIP code and the region in which they reside. Because of direct information on ZIP codes and DMAs in the USA data, this process is direct in the USA. In Europe, we follow the following procedure:

1. We link ZIP codes to NUTS2 regions by relying on the concordance tables provided by Eurostat, which can be accessed through the following link. Doing so, we rely on the NUTS2 rev. 2016 classification.

2. In the majority of cases, households reported their ZIP code which then allows for a direct link to the NUTS2 region. ZIP code are only reported from 2015 onwards in France. Given that ZIP code switches are very rare in the data, we equate their ZIP code between 2010 and 2014 to their ZIP code observed in 2015 and assume that households did not move.

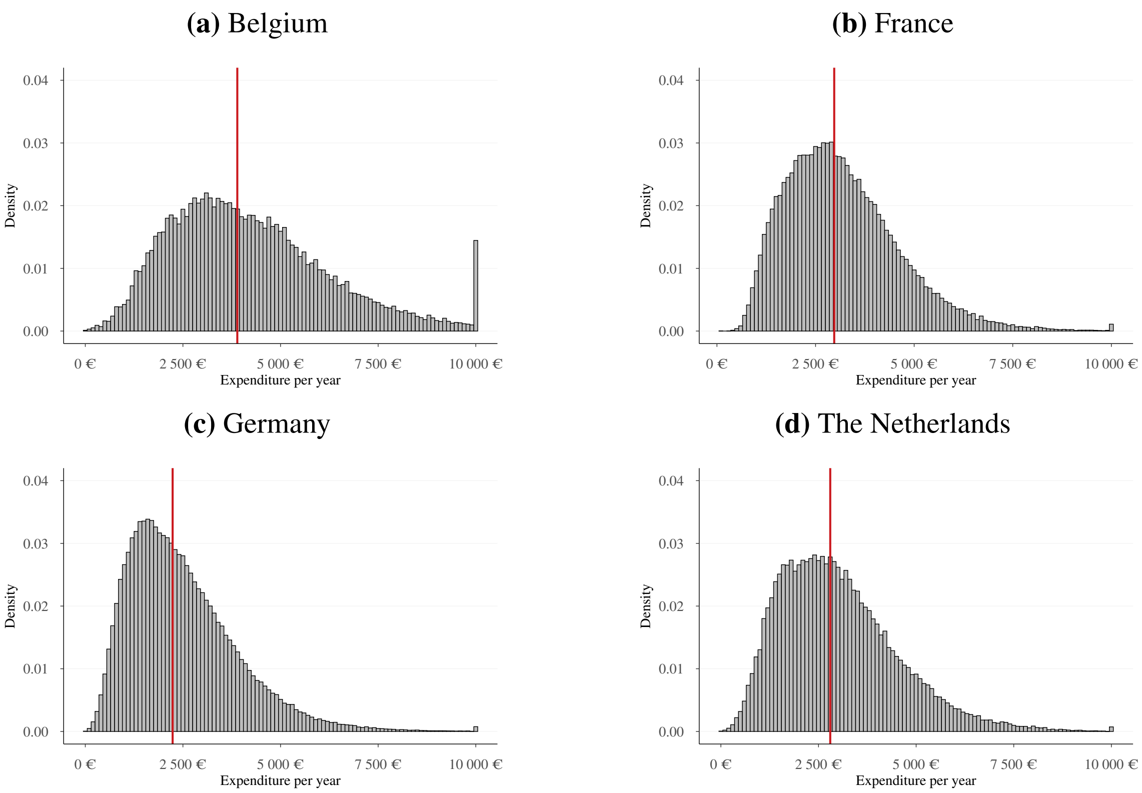
3. In case, households did not report their ZIP code, we rely on the information contained in the region of residence which is corresponds to the NUTS2 level in Belgium, Germany and the Netherlands.

4. In case, households neither reported the ZIP code or the region in which they reside, we exclude them from the sample.

Table A.7 provides an overview of the regions, households and the number of transactions we include in the sample. Other reasons for excluding households is when they did not record a purchase in all four quarters of the year.

Figure A.2: Expenditure per year

(a) Belgium **(b)** France **(c)** Germany **(d)** The Netherlands



Notes: These figures plot the distribution of average expenditure per year across households in the final sample on the 68 included categories for each country.

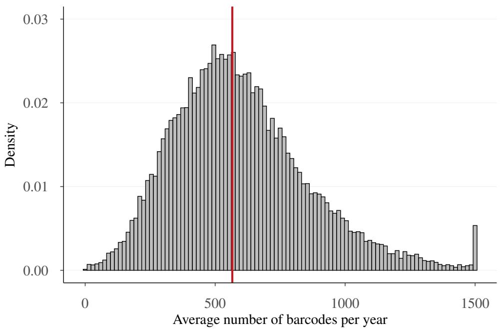
Table A.7: Sample coverage

				Included			Excluded		
Country	Nr. countries	Nr. regions	Nr. households/region	Nr households	Nr. Transactions	Exp. share	Nr households	Nr. Transactions	Exp. share
BEL	1	11	527	3,273	4,833,204	0.86	1,473	810,183	0.14
GER	1	38	1,172	23,348	29,056,307	0.88	13,525	4,119,390	0.12
FRA	1	22	1,784	7,015	8,164,680	0.58	11,130	5,808,606	0.42
NLD	1	12	1,317	8,468	13,798,990	0.91	2,329	1,301,045	0.09
USA	43	124	755	53,555	32,626,334	0.87	8,058	5,075,024	0.13

Notes: This table shows for each country (1) the number of regions that are included, (2) the average number of households that are included in a given region. To obtain these numbers, we first compute the statistics for each year and then average over the years. This table also shows the average number of households per country, the average number of transactions and the average expenditure share for the set of included and excluded consumers. Like before, we first compute the statistics for each year and then average over the years.

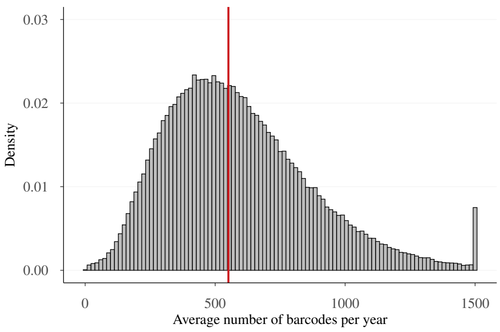
Figure A.3: Barcodes per year

(a) Belgium

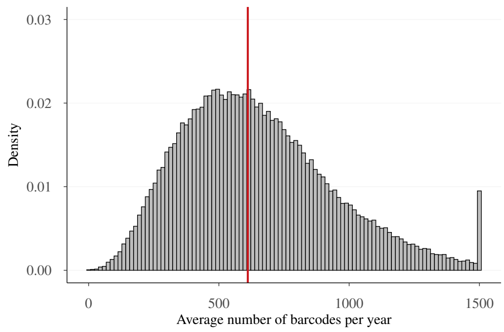


(b) France

(c) Germany



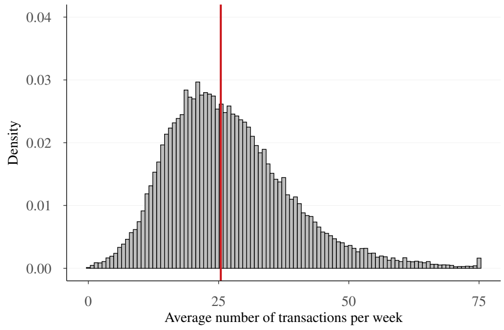
(d) The Netherlands



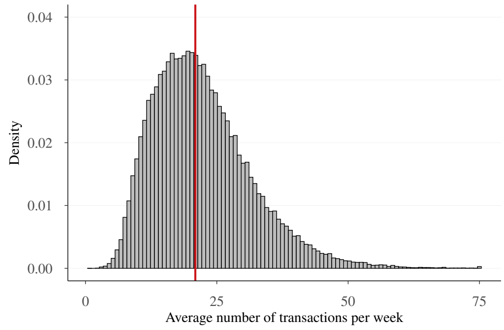
Notes: These figures plot the distribution of the average number of consumed barcodes per year across households in the final sample on the 68 included categories for each country.

Figure A.4: Purchases per week

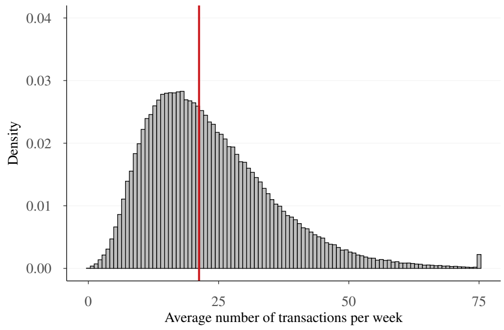
(a) Belgium



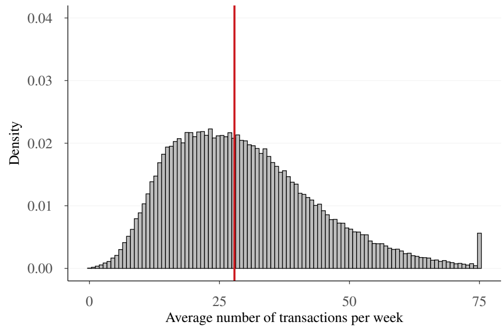
(b) France



(c) Germany

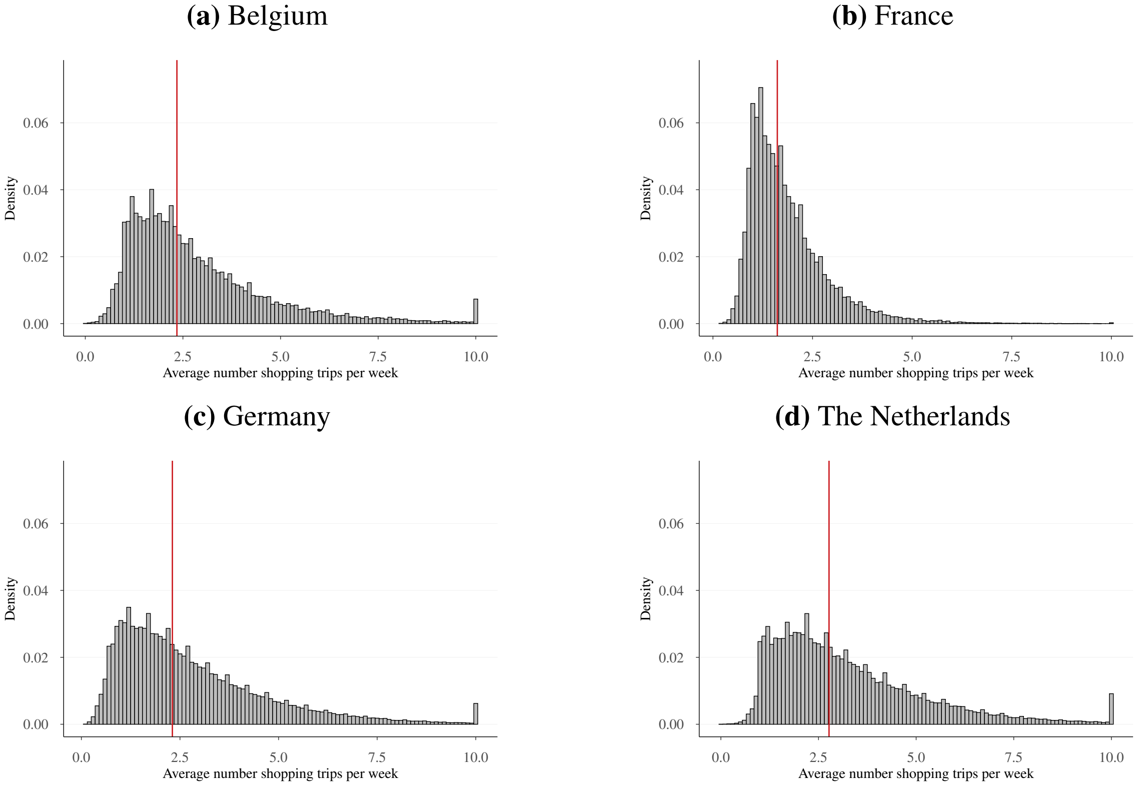


(d) The Netherlands



Notes: These figures plot the distribution of the average number of transactions barcodes per week across households in the final sample on the 68 included categories for each country.

Figure A.5: Store visits per week



Notes: These figures plot the distribution of the average number of store visits barcodes per week across households in the final sample on the 68 included categories for each country. We define a store visit as a combination of visiting a store on a certain day. Hence, visiting two different stores on the same day is counted as two store visits.

A.5 Stores

Table A.8: Stores: Overview

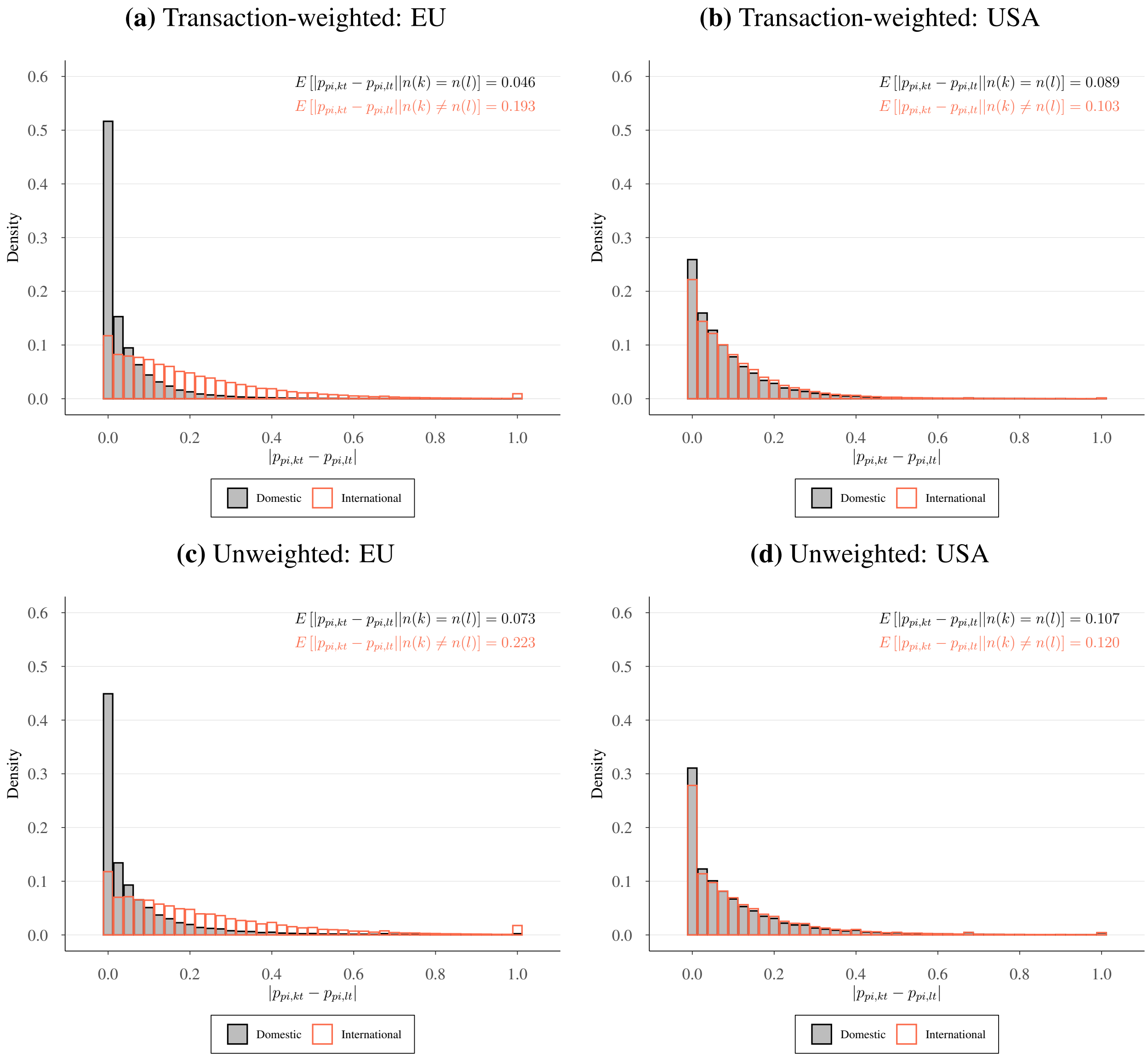
	Belgium		France		Germany		Netherlands	
Store	Sales	Trans	Sales	Trans	Sales	Trans	Sales	Trans
Grocery store	0.38	0.38	0.82	0.80	0.42	0.41	0.60	0.61
Discounter	0.44	0.49	0.11	0.15	0.39	0.48	0.28	0.32
Convenience store	0.02	0.03	0.02	0.03	0.02	0.01	0.01	0.01
Specialist store	0.12	0.09	0.03	0.01	0.17	0.11	0.10	0.05
Excluded	0.03	0.03	0.01	0.01	0.00	0.00	0.01	0.01

Notes: This table shows for each country the expenditure and transaction share across the different stores respectively.

B Reduced form evidence

B.1 LOP deviations

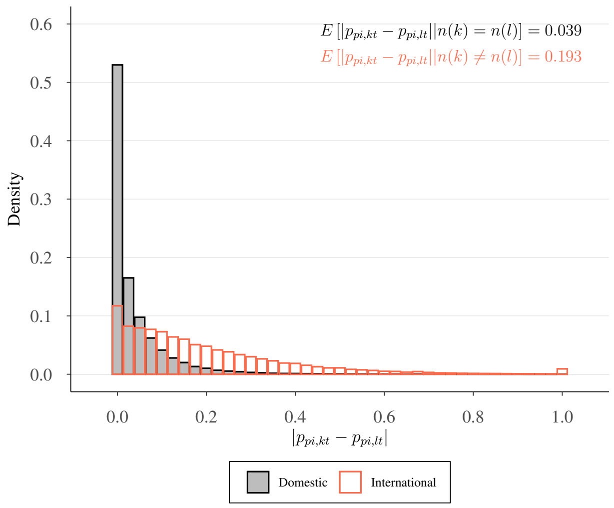
Figure B.1: Absolute LOP deviations - All varieties



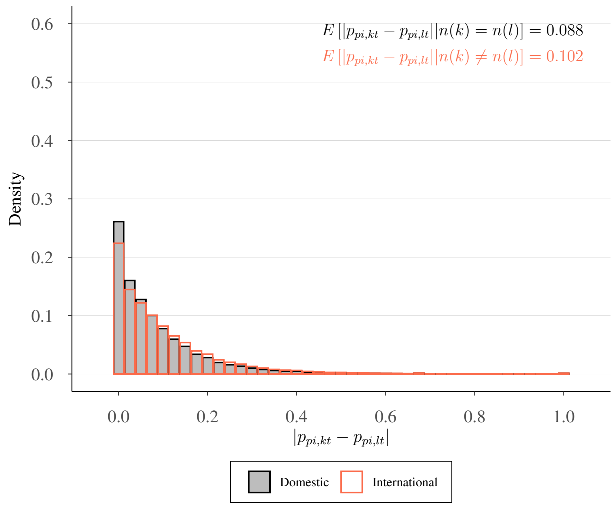
Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.2: Absolute LOP deviations - Branded and private label varieties

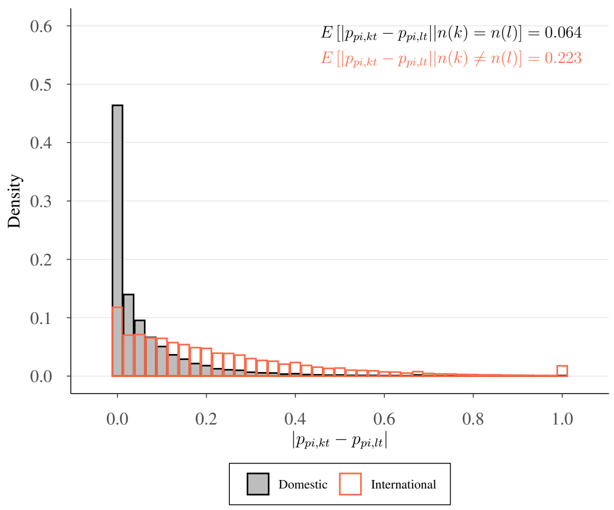
(a) Transaction-weighted: EU



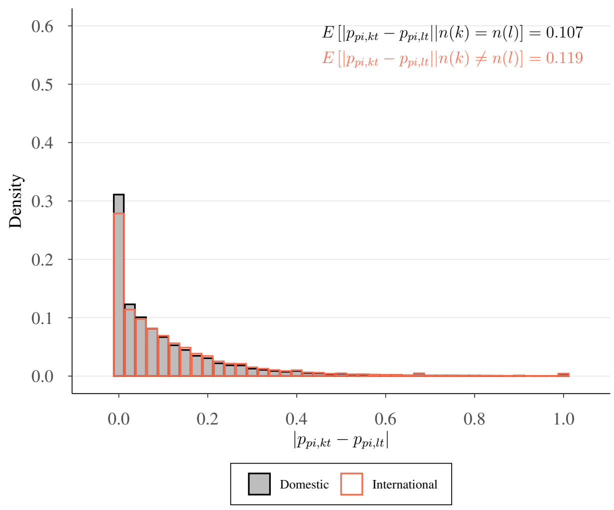
(b) Transaction-weighted: USA



(c) Unweighted: EU

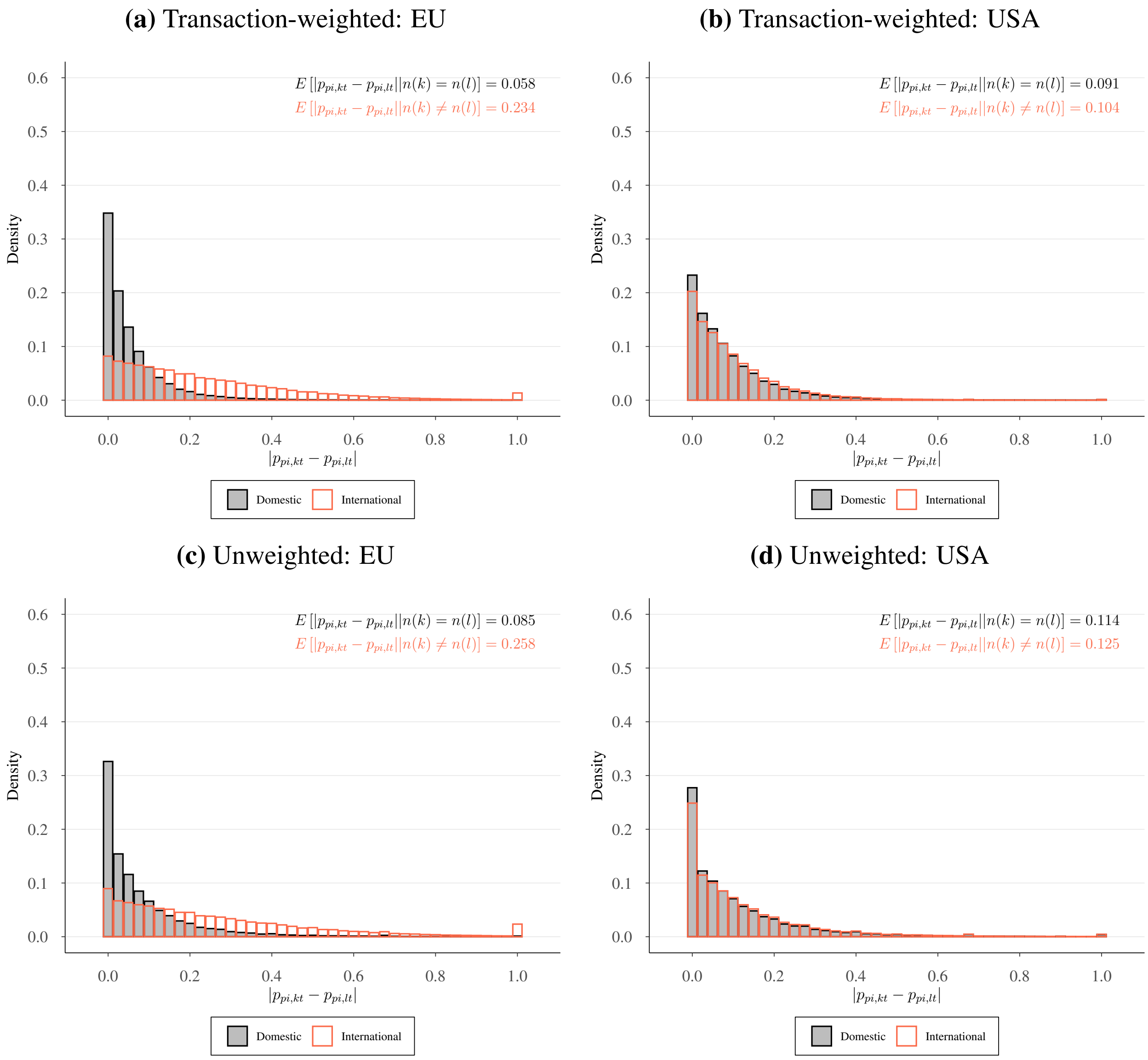


(d) Unweighted: USA



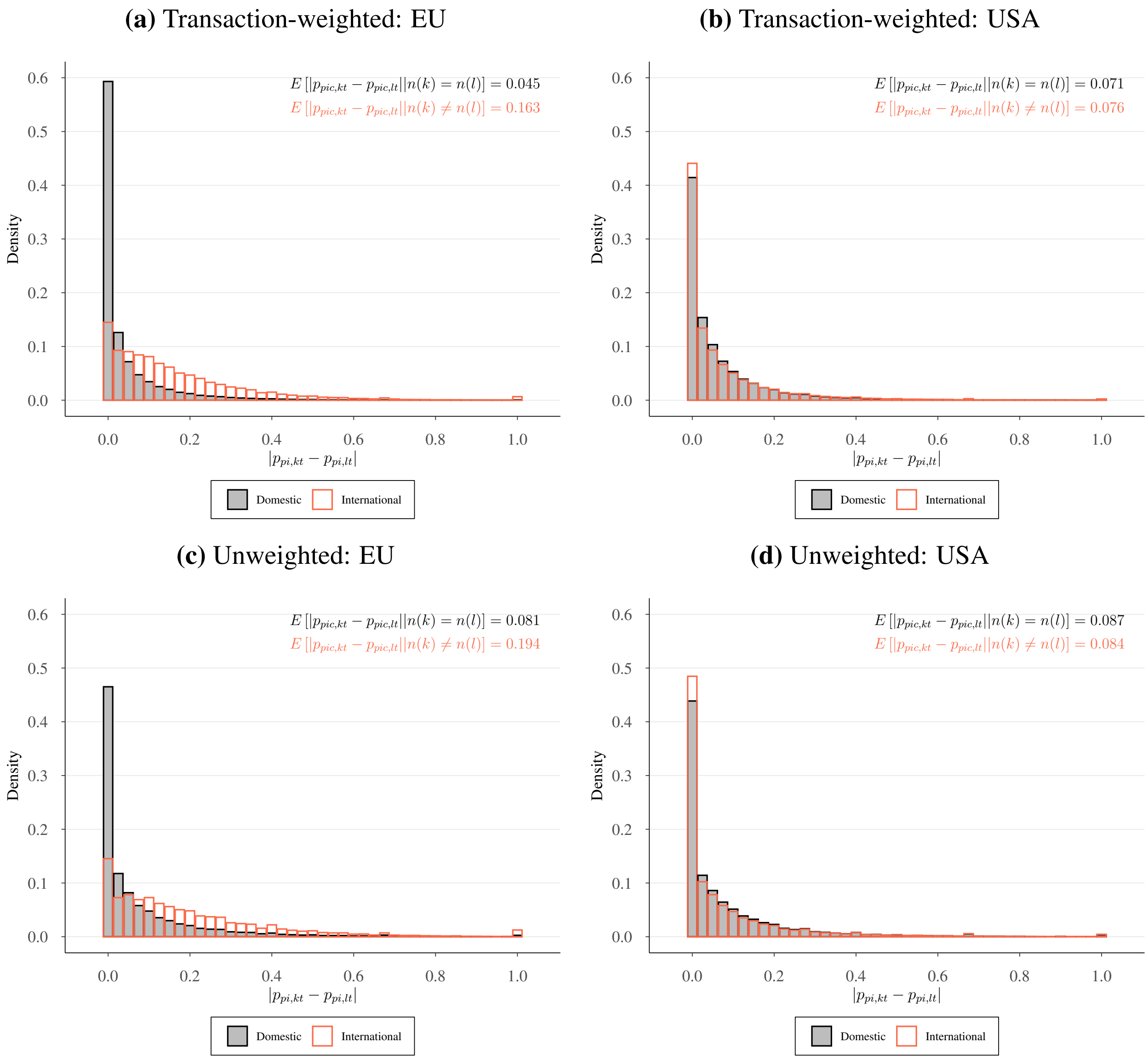
Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.3: Absolute LOP deviations - Branded varieties



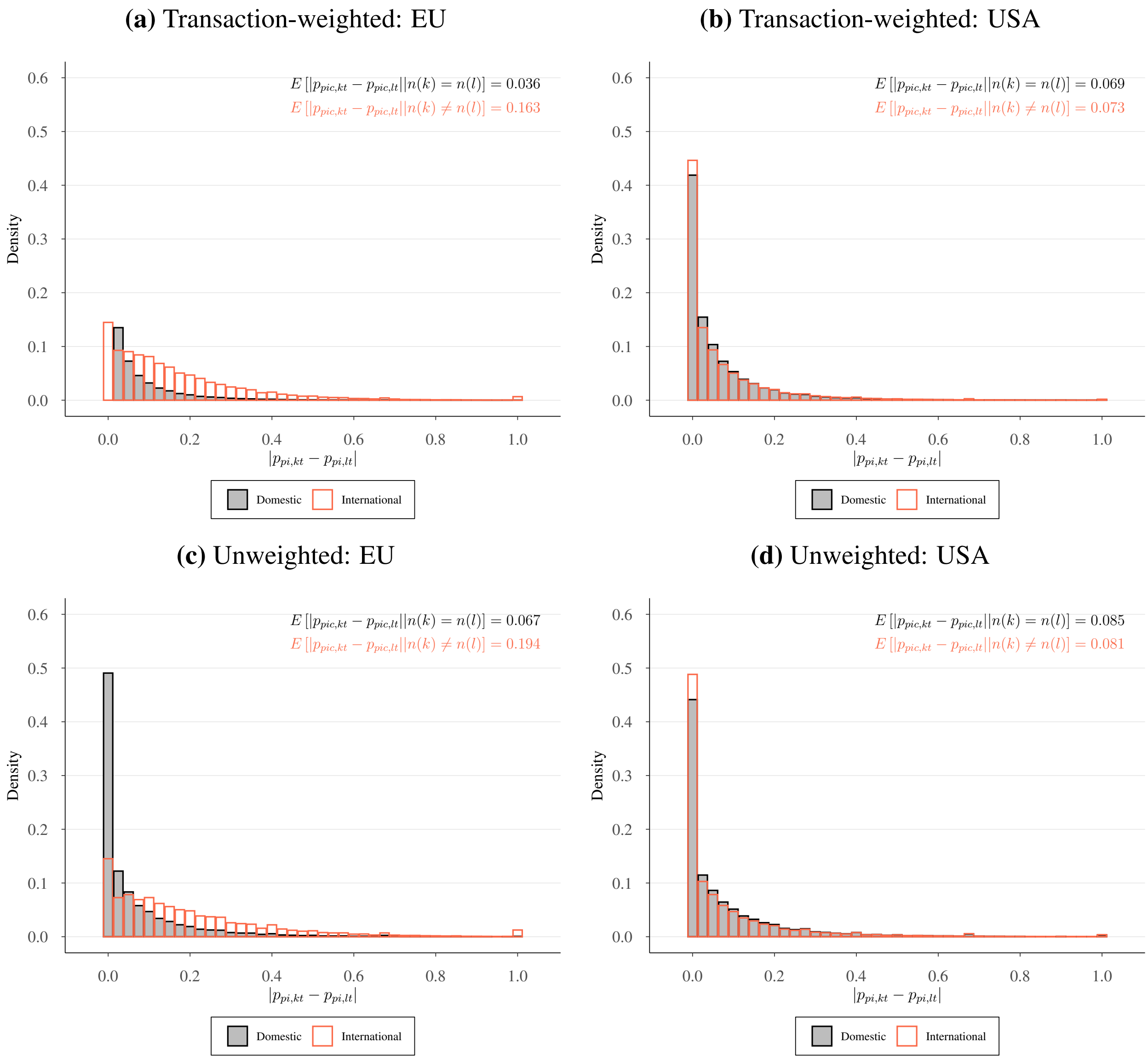
Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.4: Absolute LOP deviations - All varieties - Within store



Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.5: Absolute LOP deviations - Branded and private label varieties - Within store



(a) Transaction-weighted: EU

(b) Transaction-weighted: USA

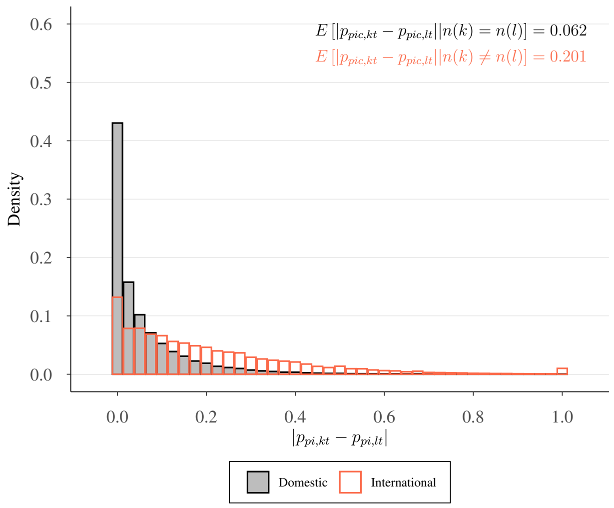
(c) Unweighted: EU

(d) Unweighted: USA

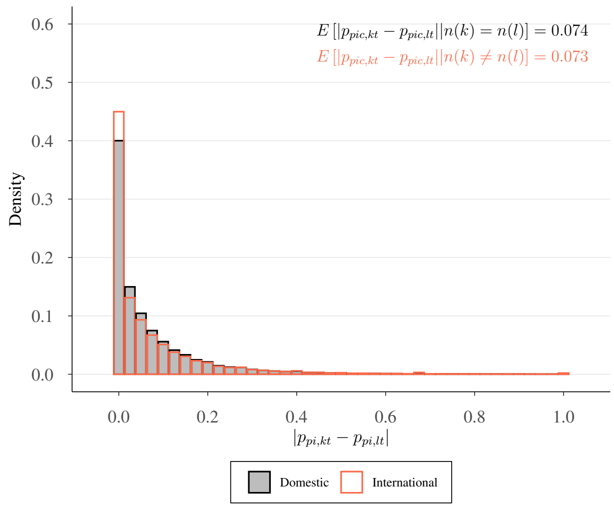
Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.6: Absolute LOP deviations - Branded varieties - Within store

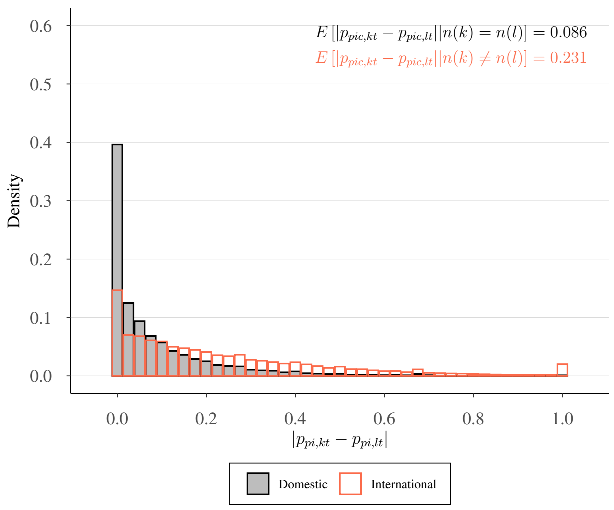
(a) Transaction-weighted: EU



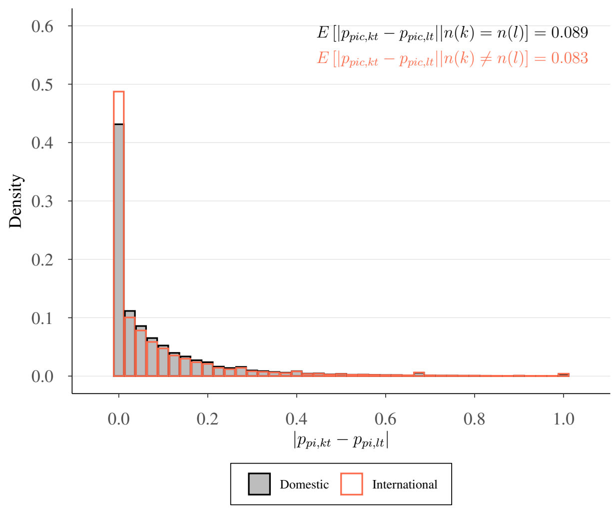
(b) Transaction-weighted: USA



(c) Unweighted: EU

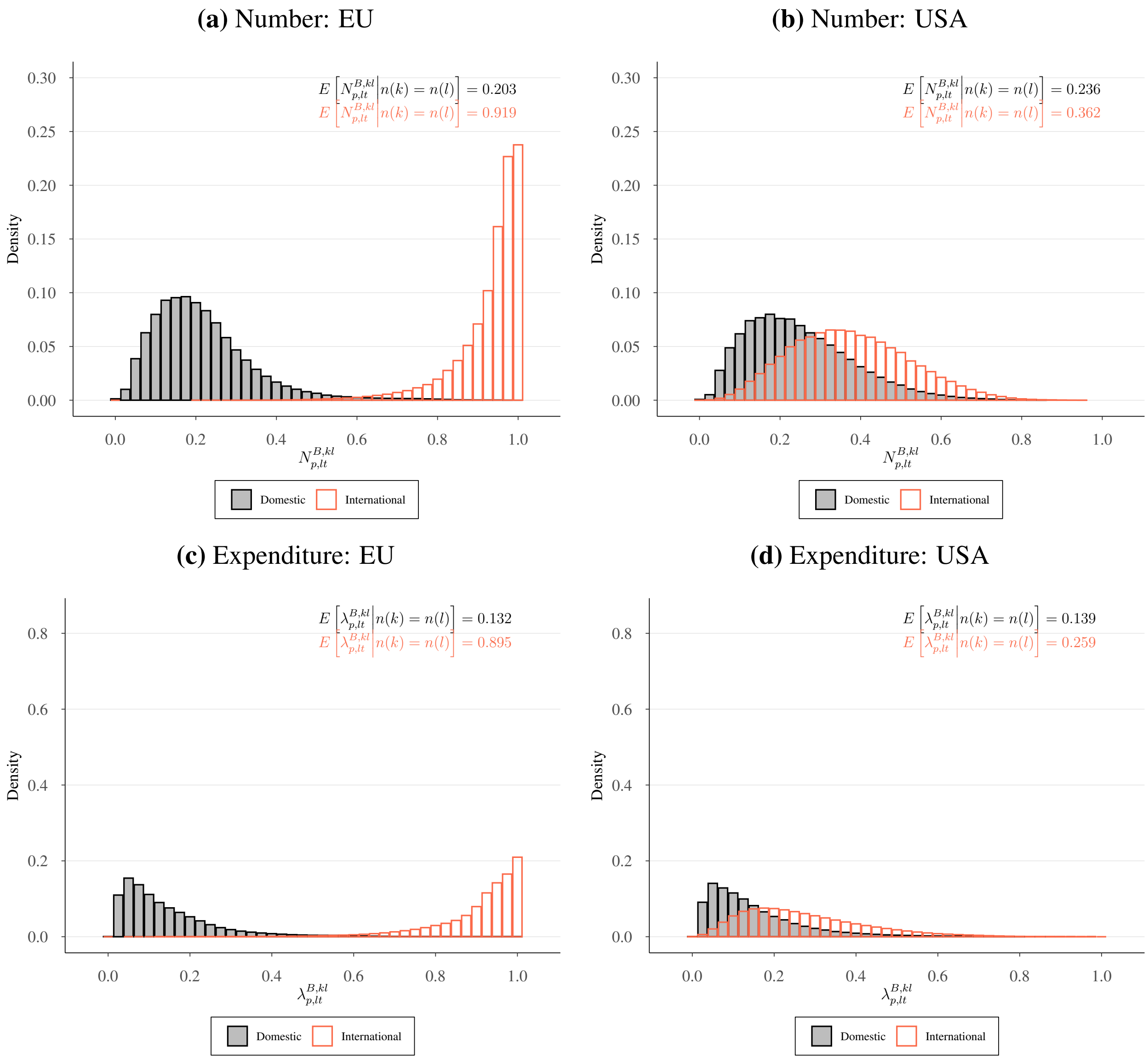


(d) Unweighted: USA



Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

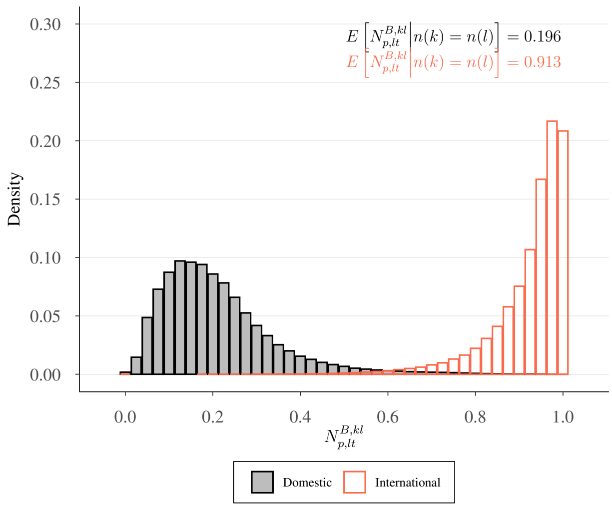
Figure B.7: Barcode availability differences - All varieties



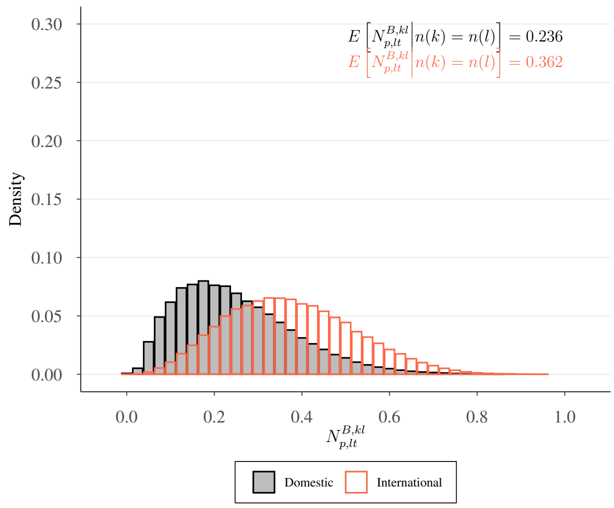
Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.8: Barcode availability differences - Branded and private label varieties

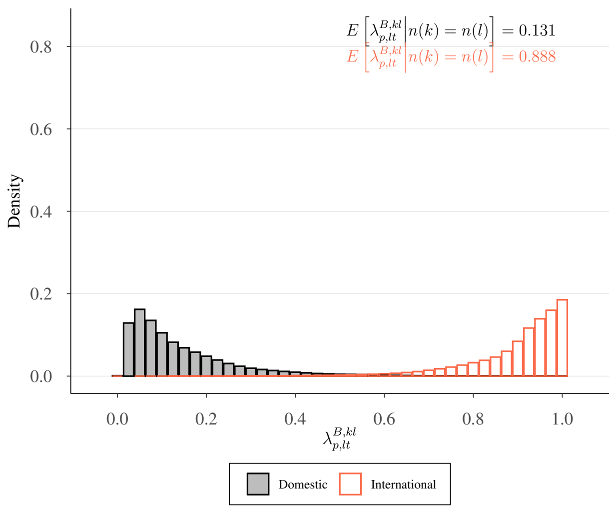
(a) Number: EU



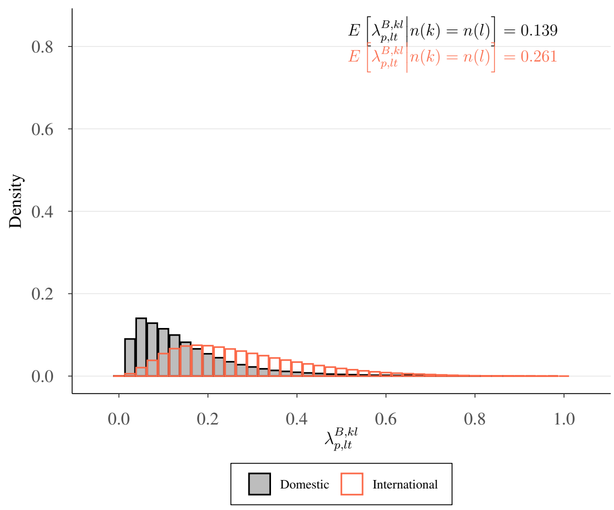
(b) Number: USA



(c) Expenditure: EU



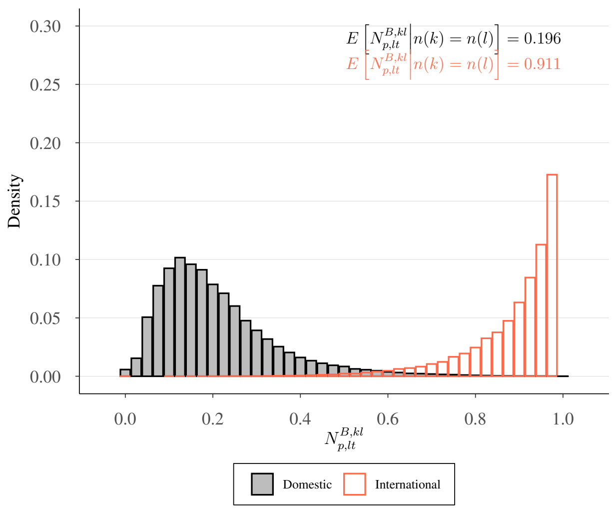
(d) Expenditure: USA



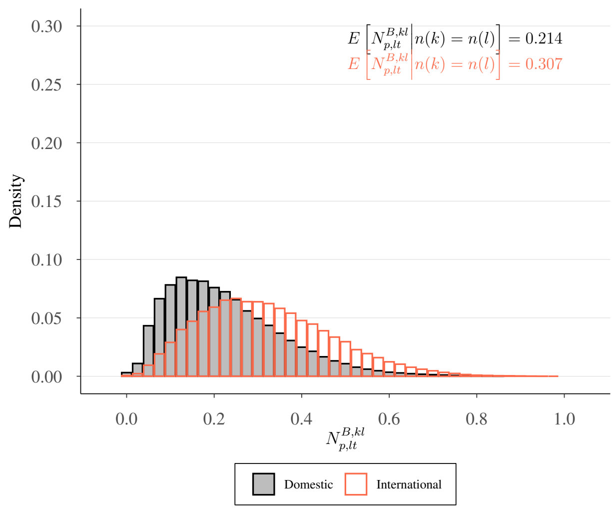
Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.9: Barcode availability differences - Branded varieties

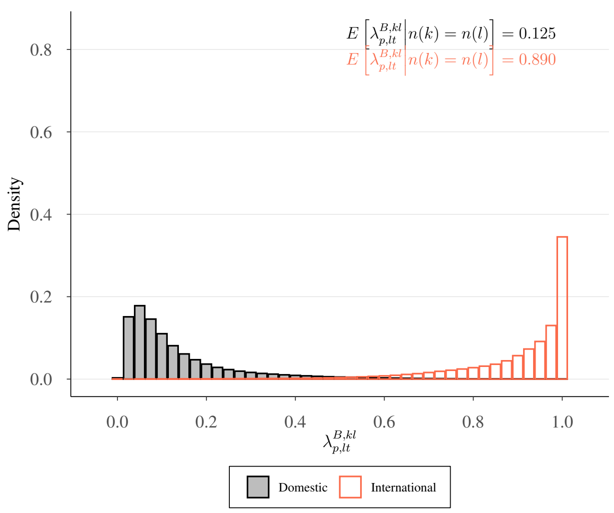
(a) Number: EU



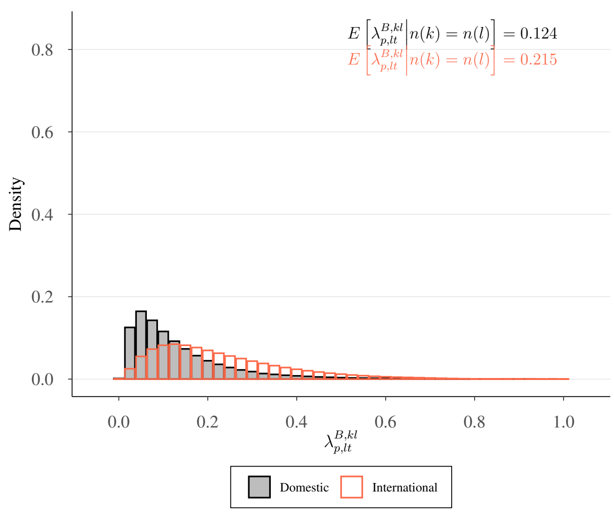
(b) Number: USA



(c) Expenditure: EU

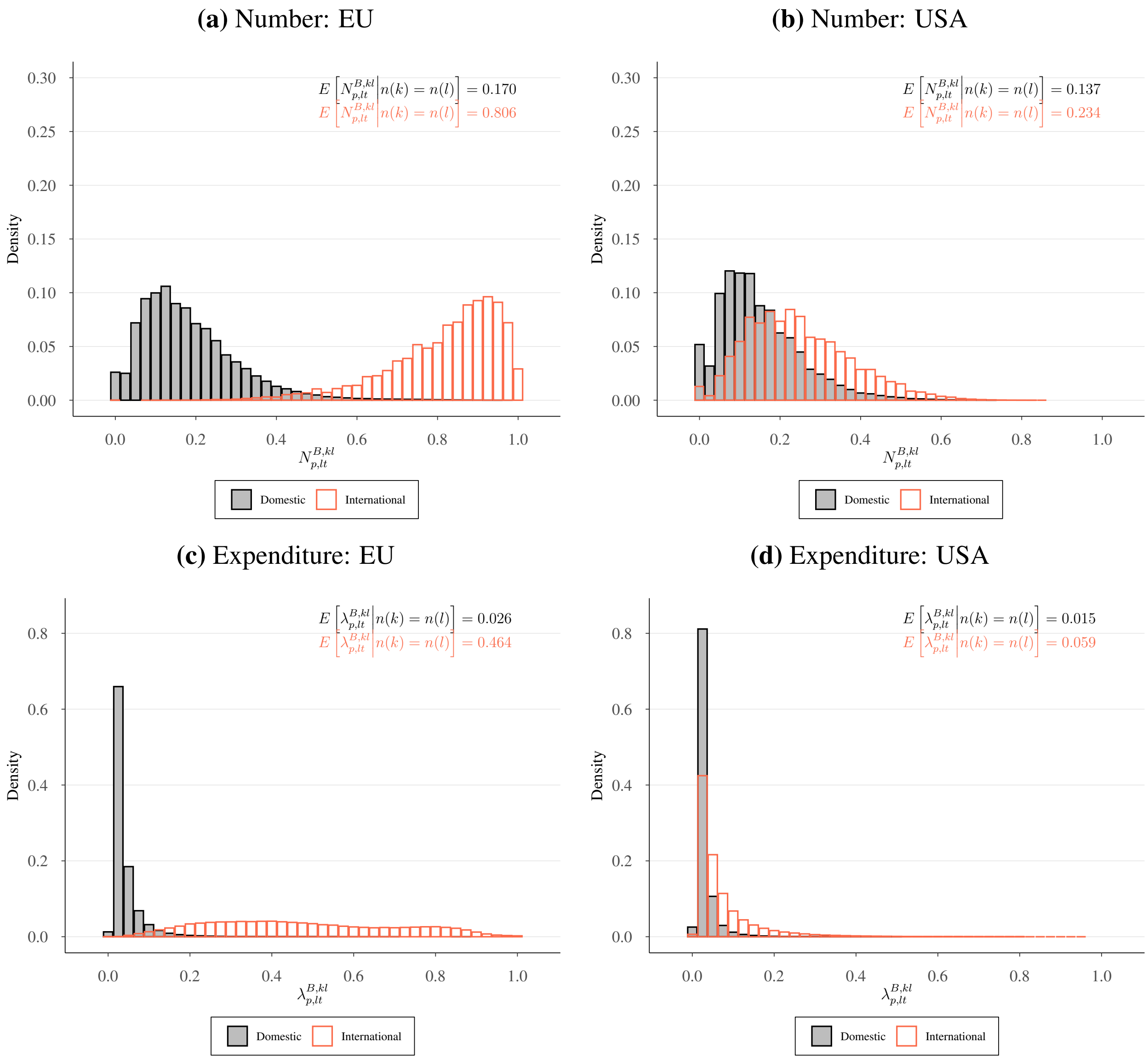


(d) Expenditure: USA



Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.10: Firm availability differences



Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Table B.1: Border effects: Price differences

y_{klt}	$\lvert p_{pi,kt} - p_{pi,lt}\rvert$						$\lvert p_{pic,kt} - p_{pic,lt}\rvert$					
	All		Branded and Priv. label		Branded		All		Branded and Priv. label		Branded	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel (a): Europe												
ln (Distance)^{kl}	.0225***	.0069***	.0246***	.0061***	.0259***	.0064***	.013***	.007***	.0133***	.0056***	.0085***	.0073***
	(.0015)	$(3.4e-04)$	(.0016)	$(3.0e-04)$	(.0017)	$(3.0e-04)$	$(8.6e-04)$	$(3.8e-04)$	$(9.2e-04)$	$(3.2e-04)$	$(4.8e-04)$	$(4.2e-04)$
Border^{kl}		.1621***		.1638***		.1945***		.1322***		.1387***		.1758***
		(.0012)		(.0011)		(.0014)		(.0011)		(.001)		(.002)
Domestic	.046	.046	.0393	.0393	.0582	.0582	.0449	.0449	.0362	.0362	.0622	.0622
Nr. obs	34,082,536	34,082,536	33,192,296	33,192,296	26,674,836	26,674,836	22,956,922	22,956,922	22,100,176	22,100,176	15,965,589	15,965,589
Within R^2	0.01	0.04	0.01	0.05	0.01	0.05	0.00	0.01	0.00	0.02	0.00	0.00
Panel (b): United States of America												
ln (Distance)^{kl}	.0071***	.0068***	.007***	.0066***	.0067***	.0064***	.0022***	.0014***	.0014***	$6.5e-04$***	$-8.8e-04$***	$-.0015$***
	$(1.9e-04)$	$(2.3e-04)$	$(1.9e-04)$	$(2.2e-04)$	$(2.0e-04)$	$(2.4e-04)$	$(2.0e-04)$	$(2.3e-04)$	$(1.9e-04)$	$(2.1e-04)$	$(2.2e-04)$	$(2.5e-04)$
Border^{kl}		.0035***		.0035***		.0024***		.0056***		.0057***		.0046***
		$(6.5e-04)$		$(6.4e-04)$		$(6.6e-04)$		$(8.6e-04)$		$(8.3e-04)$		$(9.8e-04)$
Domestic	.0887	.0887	.088	.088	.0913	.0913	.0709	.0709	.0688	.0688	.0742	.0742
Nr. obs	123,914,760	123,914,760	123,682,872	123,682,872	118,766,672	118,766,672	94,426,480	94,426,480	93,310,768	93,310,768	85,243,608	85,243,608
Within R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
θ_l	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
θ_l	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$\lambda_{p,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents the results from Equation 1 with OLS. Panel (a) presents the results for European regions and panel (b) for US regions. Columns (1)-(2) present the results for the variance of LOP and columns (3)-(10) show the results for various measures of product availability differences. Columns (3)-(6) focus on the variety level and columns (7)-(10) provide estimates for the firm-level measures of product availability measures. Columns (3), (5),(7) and (9) show count-based estimates. Columns (4), (6),(8) and (10) show count-based estimates. Alongside the estimates, we provide the average value of the left-hand variable for intranational regions under "intra", the number of observations and the R^2 of the regression after partialling out the fixed effects. We cluster standard errors at the region pair and present them in brackets below the coefficient estimates. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

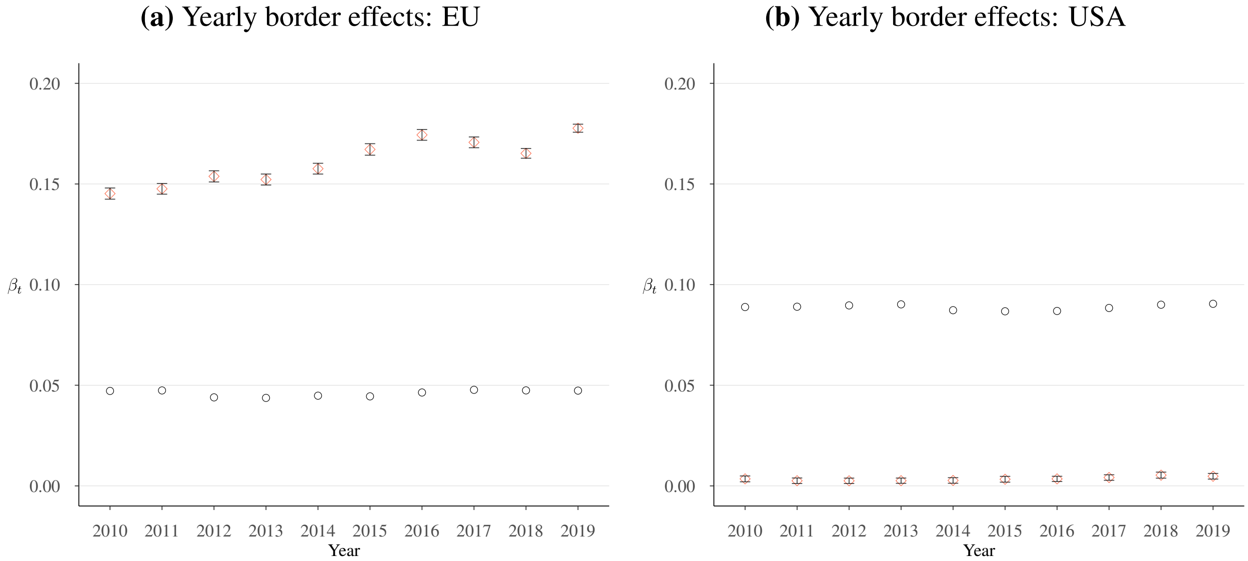
Table B.2: Border effects: Barcode availability differences

y_{klt}	All				Branded and Priv. label				Branded			
	$N_{p,lt}^{B,kl}$		$\Lambda_{p,lt}^{B,kl}$		$N_{p,lt}^{B,kl}$		$\Lambda_{p,lt}^{B,kl}$		$N_{p,lt}^{B,kl}$		$\Lambda_{p,lt}^{B,kl}$	
PANEL (A): EUROPE												
ln (Distance)^{kl}	.4172***	.0444***	.4487***	.0518***	.4205***	.0469***	.449***	.0556***	.413***	.0367***	.4468***	.0433***
	(.0092)	(.0022)	(.01)	(.0023)	(.0093)	(.0023)	(.0099)	(.0024)	(.0092)	(.0025)	(.0099)	(.0026)
Border^{kl}		.7081***		.7539***		.7096***		.7473***		.7149***		.7663***
		(.0028)		(.0026)		(.003)		(.0028)		(.0032)		(.0031)
Domestic	.203	.203	.1319	.1319	.1962	.1962	.1314	.1314	.1958	.1958	.125	.125
Nr. obs	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670	4,627,588	4,627,588	4,627,588	4,627,588
Within R^2	0.45	0.94	0.45	0.93	0.45	0.94	0.46	0.93	0.43	0.92	0.43	0.91
PANEL (B): UNITED STATES OF AMERICA												
ln (Distance)^{kl}	.063***	.0613***	.0626***	.062***	.063***	.0614***	.0631***	.0626***	.0481***	.0476***	.0494***	.0499***
	$(5.3e-04)$	$(5.8e-04)$	$(5.9e-04)$	$(6.2e-04)$	$(5.3e-04)$	$(5.8e-04)$	$(5.9e-04)$	$(6.3e-04)$	$(4.1e-04)$	$(4.3e-04)$	$(4.7e-04)$	$(4.9e-04)$
Border^{kl}		.0152***		.0049*		.0152***		.0048*		.0051***		−.005**
		(.0025)		(.0027)		(.0025)		(.0027)		(.0019)		(.0021)
Domestic	.2364	.2364	.1387	.1387	.2362	.2362	.139	.139	.2141	.2141	.1237	.1237
Nr. obs	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360
Within R^2	0.29	0.29	0.18	0.18	0.29	0.29	0.19	0.19	0.19	0.19	0.12	0.12
θ_l	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
θ_l	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
$\lambda_{p,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents the results from Equation 1 with OLS. Panel (a) presents the results for European regions and panel (b) for US regions. Columns (1)-(2) present the results for the variance of LOP and columns (3)-(10) show the results for various measures of product availability differences. Columns (3)-(6) focus on the variety level and columns (7)-(10) provide estimates for the firm-level measures of product availability measures. Columns (3), (5),(7) and (9) show count-based estimates. Columns (4), (6),(8) and (10) show count-based estimates. Alongside the estimates, we provide the average value of the left-hand variable for intranational regions under "intra", the number of observations and the R^2 of the regression after partialling out the fixed effects. We cluster standard errors at the region pair and present them in brackets below the coefficient estimates. Reported significance levels are at the $p < 0.1^*$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

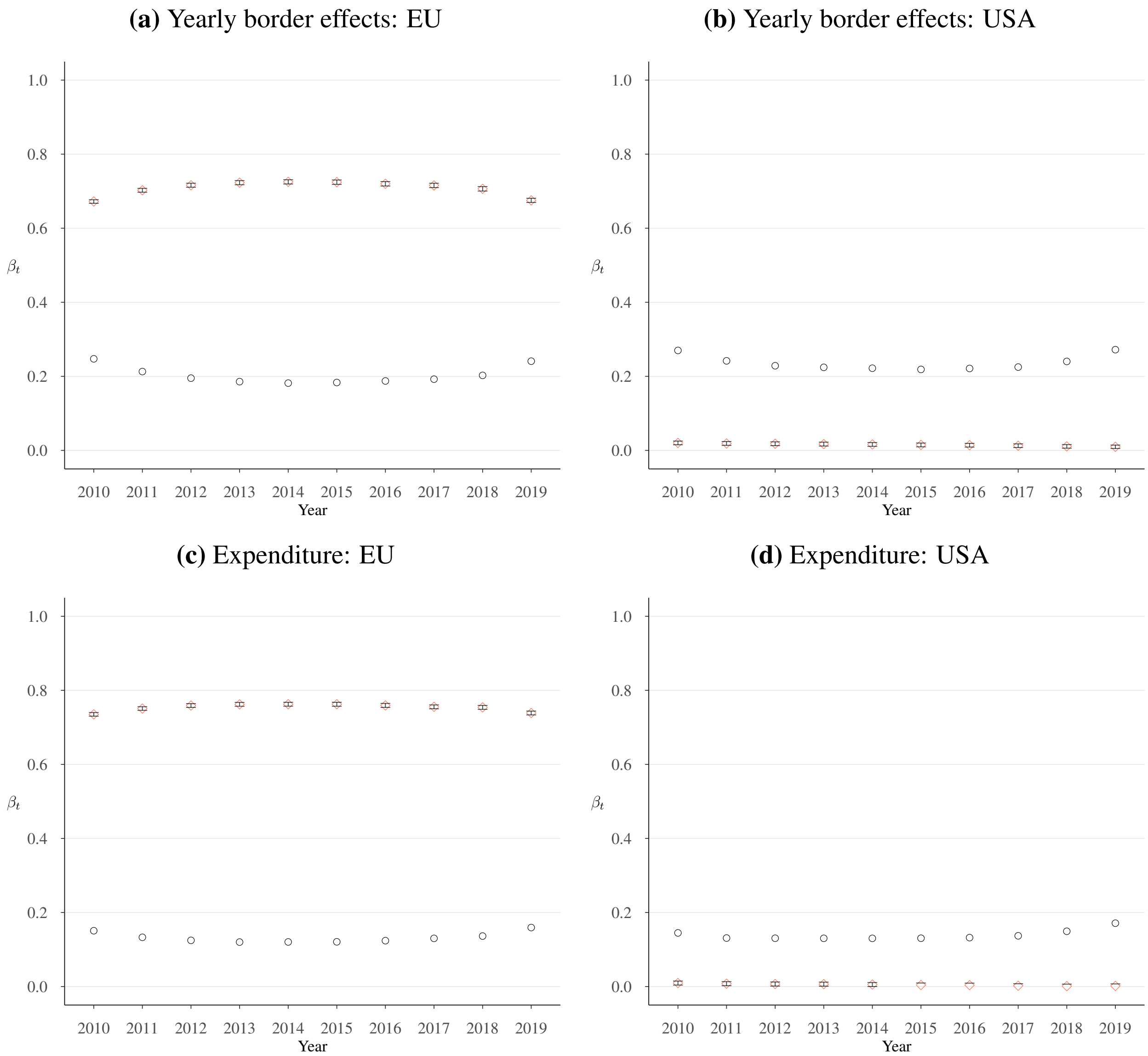
B.2 Robustness of Table 1

Figure B.11: Yearly border effects: LOP deviations



Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

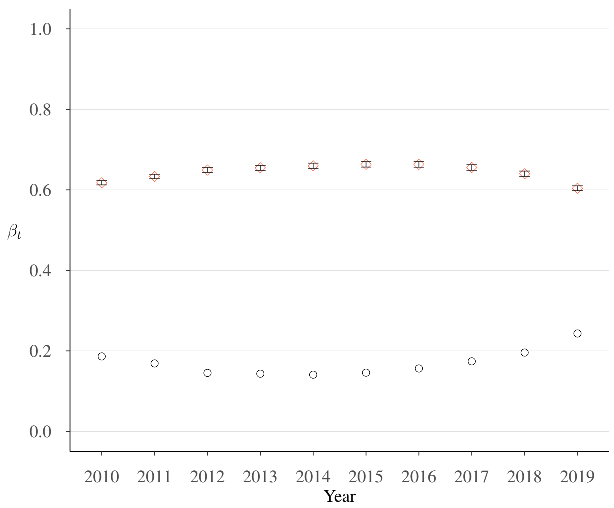
Figure B.12: Yearly border effects: Barcode availability differences - All varieties



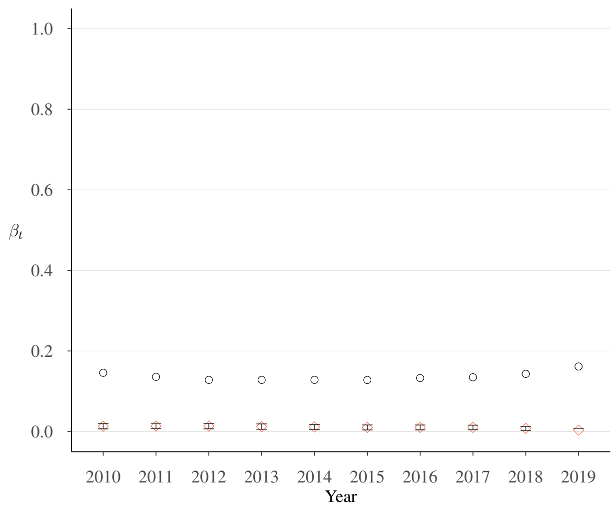
Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.13: Yearly border effects: Firm Availability differences

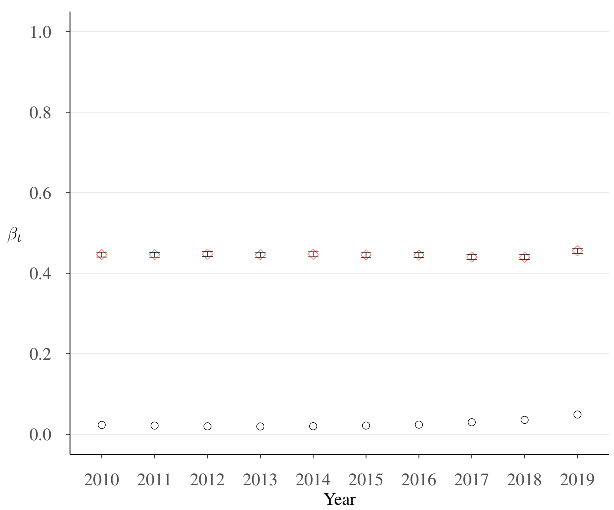
(a) Yearly border effects: EU



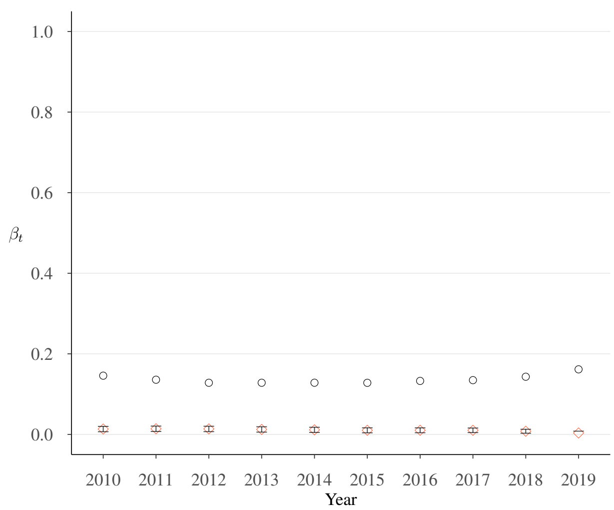
(b) Yearly border effects: USA



(c) Expenditure: EU



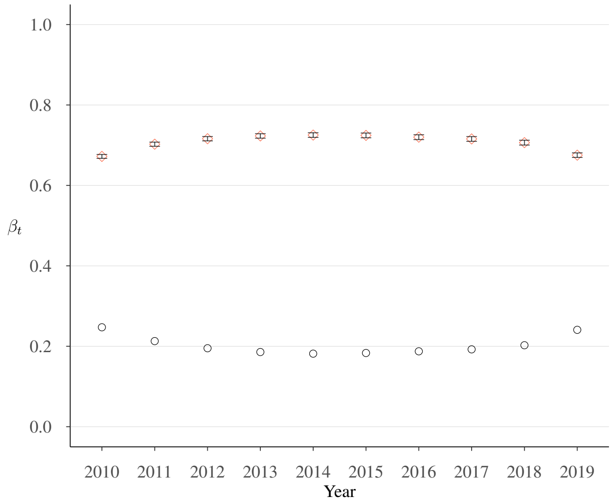
(d) Expenditure: USA



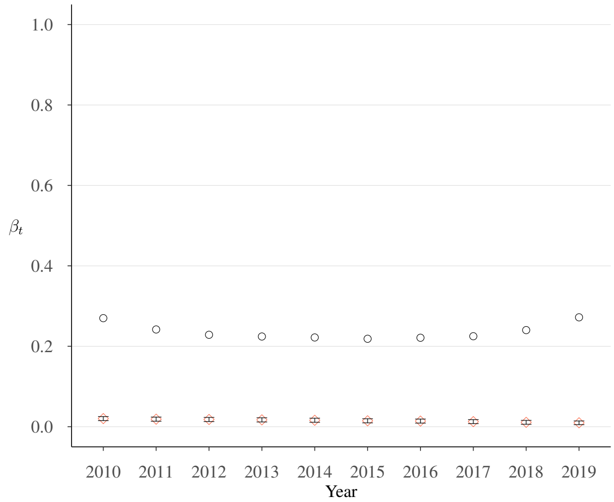
Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.14: Yearly border effects: Availability differences - All varieties

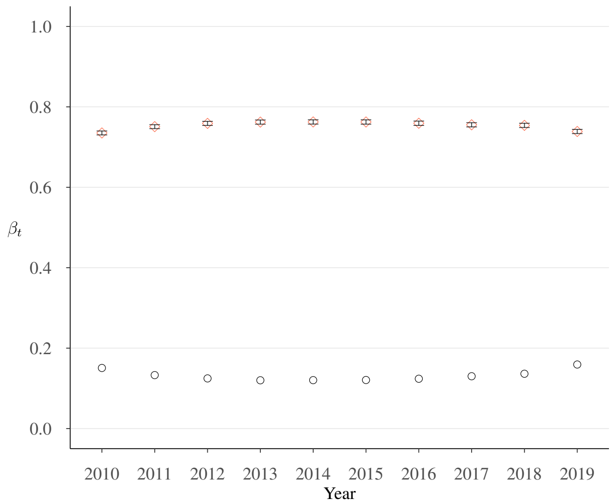
(a) Yearly border effects: EU



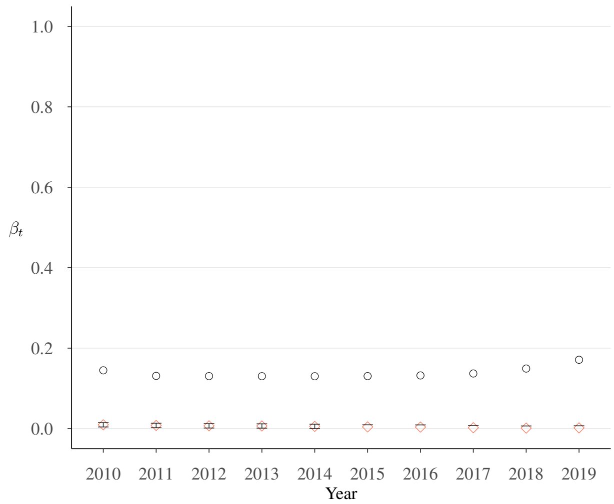
(b) Yearly border effects: USA



(c) Expenditure: EU

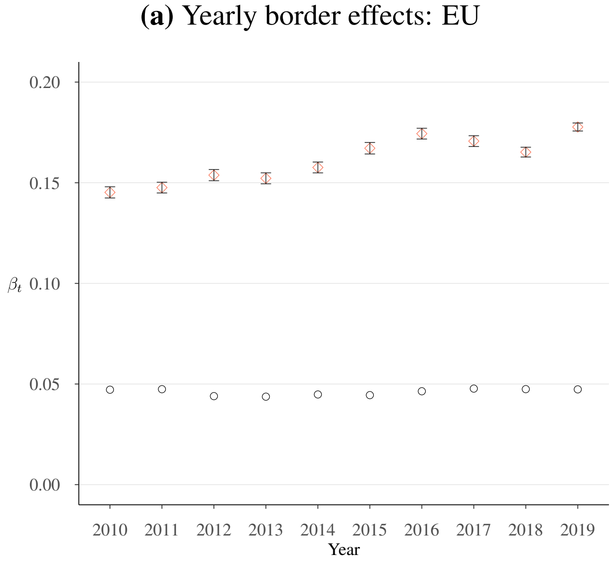


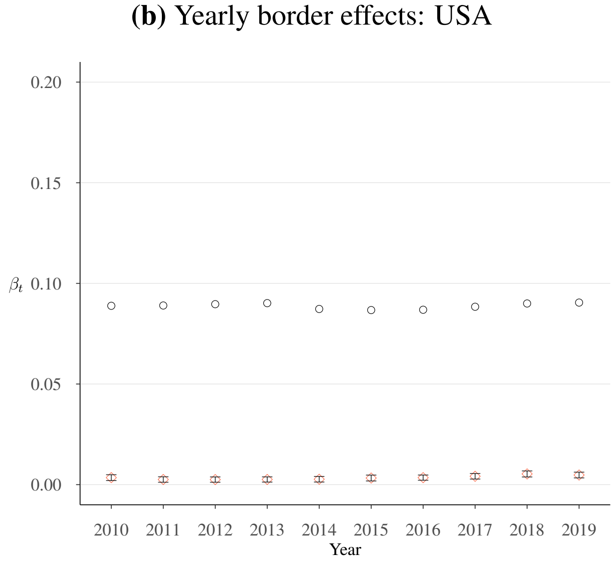
(d) Expenditure: USA



Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Figure B.15: Absolute LOP deviations - All varieties





Notes: This figure plots the distribution of the absolute LOP deviations across variety-year-NUTS2-region pairs. The grey bars plot the conditional distribution for intranational pairs, and the red bars do the same for international pairs. We compute these distributions in two steps. First, we compute LOP deviations and winsorize the distribution symmetrically at 1 log point. Second, we bin the variance into 40 separate bins and compute for each bin the number of observations that fall into each bin. Panel (a) replicates the result we show in the paper and is based on pooling across households and stores when computing price differences. Panel (b) computes price differences for identical product varieties within store types. Panel (c) computes price differences for identical product varieties within household types. Panel (d) computes price differences for identical product varieties within stores and household types.

Table B.3: Border effects: Price and product availability differences - Time trend

y_{klt}	$\lvert p_{pi,kt} - p_{pi,lt}\rvert$		$N_{lt}^{B,kl}$		$\lambda_{lt}^{B,kl}$		$N_{lt}^{F,kl}$		$\lambda_{lt}^{F,kl}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PANEL (A): EUROPE										
Border^{kl}	.1711***	.1621***	.7438***	.7081***	.7955***	.7539***	.6707***	.6441***	.4729***	.4459***
	(.0011)	(.0012)	(.0024)	(.0028)	(.0021)	(.0026)	(.0027)	(.0032)	(.0028)	(.0032)
ln (Distance)^{kl}		.0068***		.0444***		.0518***		.0331***		.0336***
		$(3.4e-04)$		(.0022)		(.0023)		(.0025)		(.0024)
Trend$_t$	$4.2e-04$***	$4.2e-04$***	$-8.3e-04$***	$-8.3e-04$***	$2.3e-04$***	$2.3e-04$***	.0046***	.0046***	.0015***	.0015***
	$(3.0e-05)$	$(3.0e-05)$	$(3.2e-05)$	$(3.2e-05)$	$(3.6e-05)$	$(3.6e-05)$	$(5.9e-05)$	$(5.9e-05)$	$(4.3e-05)$	$(4.3e-05)$
Domestic	.046	.046	.203	.203	.1319	.1319	.17	.17	.0263	.0263
Nr. obs	34,082,536	34,082,536	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670	4,627,670
Within R^2	0.04	0.04	0.94	0.94	0.93	0.93	0.89	0.90	0.67	0.67
PANEL (B): UNITED STATES OF AMERICA										
Border^{kl}	.0153***	.0035***	.1202***	.0152***	.111***	.0049*	.0972***	.0107***	.0411***	-.002
	$(6.7e-04)$	$(6.5e-04)$	(.0037)	(.0025)	(.0038)	(.0027)	(.0035)	(.003)	(.0016)	(.0016)
ln (Distance)^{kl}		.0068***		.0613***		.062***		.0506***		.0252***
		$(2.3e-04)$		$(5.8e-04)$		$(6.2e-04)$		$(5.0e-04)$		$(3.2e-04)$
Trend$_t$	-2.4e-05	$-2.8e-05$*	$-.0023$***	$-.0023$***	$6.3e-04$***	$6.3e-04$***	$1.8e-04$***	$1.8e-04$***	$7.8e-05$***	$7.8e-05$***
	$(1.5e-05)$	$(1.5e-05)$	$(2.0e-05)$	$(2.0e-05)$	$(2.1e-05)$	$(2.1e-05)$	$(3.3e-05)$	$(3.3e-05)$	$(1.1e-05)$	$(1.1e-05)$
Domestic	.0887	.0887	.203	.2364	.1387	.1387	.1366	.1366	.015	.015
Nr. obs	123,914,760	123,914,760	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360	10,371,360
Within R^2	0.00	0.00	0.07	0.27	0.03	0.17	0.04	0.16	0.01	0.07
θ_l	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
θ_l	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
λ_p	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table presents the results from Equation 1 with OLS and an estimated time trend. Panel (a) presents the results for European regions and panel (b) for US regions. Columns (1)-(2) present the results for the variance of LOP and columns (3)-(10) show the results for various measures of product availability differences. Columns (3)-(6) focus on the variety level and columns (7)-(10) provide estimates for the firm-level measures of product availability measures. Columns (3), (5),(7) and (9) show count-based estimates. Columns (4), (6),(8) and (10) show count-based estimates. Alongside the estimates, we provide the average value of the left-hand variable for domestic regions under "Domestic", the number of observations and the R^2 of the regression after partialling out the fixed effects. We cluster standard errors at the region pair and present them in brackets below the coefficient estimates. Reported significance levels are at the $p < 0.1^*$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

C Theory Appendix

C.1 Cost-of-living decomposition

In this section, we provide a stepwise derivation of the decomposition of cost-of-living differences.

Definitions Define the share spend in region l at time t on firms that sell both in region l and region k in category p, $\lambda^{kl}_{p,lt}$, and the share spend in region l in at time t on common varieties sold by firm f between region l and region k in product category p, $\lambda^{kl}_{pf,lt}$, as:

$$\lambda^{kl}_{p,lt} \equiv \frac{\sum_{f\in\Omega^{kl}_p} P_{pf,lt}C_{pf,lt}}{\sum_{f\in\Omega_{p,lt}} P_{pf,lt}C_{pf,lt}}, \qquad \lambda^{kl}_{pf,lt} \equiv \frac{\sum_{i\in\Omega^{kl}_{pf}} P_{pfi,lt}C_{pfi,lt}}{\sum_{i\in\Omega_{pf,lt}} P_{pfi,lt}C_{pfi,lt}},$$

where Ω^{kl}_p is the set of firms that sell both to region l and region k and $\Omega_{p,lt}$ is the set all firms selling to region l at time t in category p, $P_{pf,lt}$ is the firm-level price index defined in the main body of the text and $C_{pf,lt}$ is the corresponding firm-level consumption level. Likewise, Ω^{kl}_{pf} is the set of varieties sold by firm f that are available in both region l and region k, $\Omega_{pf,lt}$ is the set all varieties that are available in region l at time t in category p sold by firm f, $P_{pfi,lt}$ is the price of variety i in region l at time t and $C_{pfi,lt}$ is the corresponding consumption level. In addition, define for all firms that sell in region l and k in category p the common market share and for all common varieties the common market share in region l at time t in category p as:

$$S^{kl}_{pf,lt} \equiv \frac{P_{pf,lt}C_{pf,lt}}{\sum_{f\in\Omega^{kl}_p} P_{pf,lt}C_{pf,lt}}, \qquad S^{kl}_{pfi,lt} \equiv \frac{P_{pfi,lt}C_{pfi,lt}}{\sum_{i\in\Omega^{kl}_{pf}} P_{pfi,lt}C_{pfi,lt}}.$$

Then, we can write the regular market shares as the combination of the common market share and the share spent on the common choice set. For the firm-level market share:

$$\begin{aligned}
S_{pf,lt} &= \frac{P_{pf,lt}C_{pf,lt}}{\sum_{f\in\Omega^{kl}_p} P_{pf,lt}C_{pf,lt}}, \qquad \forall\, f \in \Omega^{kl}_p \\
&= \frac{P_{pf,lt}C_{pf,lt}}{\sum_{f\in\Omega^{kl}_p} P_{pf,lt}C_{pf,lt}} \frac{\sum_{f\in\Omega^{kl}_p} P_{pf,lt}C_{pf,lt}}{\sum_{f\in\Omega_{p,lt}} P_{pf,lt}C_{pf,lt}}, \qquad \forall\, f \in \Omega^{kl}_p \\
&= \frac{P_{pf,lt}C_{pf,lt}}{\sum_{\Omega^{kl}_p} P_{pf,lt}C_{pf,lt}} \frac{\sum_{f\in\Omega^{kl}_p} P_{pf,lt}C_{pf,lt}}{\sum_{f\in\Omega_{p,lt}} P_{fplt}C_{pf,lt}} \qquad \forall\, f \in \Omega^{kl}_p.
\end{aligned}$$

Therefore, we can write the market shares for each common firm and variety:

$$S_{pf,lt} = S^{kl}_{pf,lt}\lambda^{kl}_{p,lt} \quad \forall\, f \in \Omega^{kl}_p, \qquad\qquad S_{pfi,lt} = S^{kl}_{pfi,lt}\lambda^{kl}_{pf,lt} \quad \forall\, i \in \Omega^{kl}_{pf}.$$

Cost-of-living decomposition Using these definitions, we decompose cost-of-living differences $\Delta\text{CLE}_{ll',t}$ between regions l and k at time t:

$$
\begin{aligned}
\Delta\text{CLE}_t &\equiv \ln e(\boldsymbol{P}_{kt}, U_{lt}) - \ln e(\boldsymbol{P}_{lt}, U_{lt}) \\
&= \ln \frac{e(\boldsymbol{P}_{kt}, U_{lt})}{e(\boldsymbol{P}lt, Ult)} \\
&= \ln \frac{e(\boldsymbol{P}_{kt}, 1)}{e(\boldsymbol{P}_{lt}, 1)} \\
&= \ln \prod_{p\in\mathcal{P}} \left[\frac{P_{p,kt}}{P_{p,lt}}\right]^{\alpha_p} \\
&= \sum_{p\in\mathcal{P}} \alpha_p (\ln P_{p,kt} - \ln P_{p,lt}),
\end{aligned}
$$

where we have used the assumption of homothetic preferences and the assumption of Cobb-Douglas preferences across categories. Note that from Shephard's lemma, we can write firm-level and variety-level market shares as:

$$
S_{pf,lt} = \frac{C_{fplt} P_{pf,lt}}{\sum_{f\in\Omega_{p,lt}} P_{fplt} C_{pf,lt}} = \frac{\left(\frac{P_{pf,lt}}{\xi_{pf,lt}}\right)^{1-\eta_p}}{P_{p,lt}^{1-\eta_p}}, \qquad S_{pfi,lt} = \frac{C_{pfi,lt} P_{pfi,lt}}{\sum_{i\in\Omega_{pf,lt}} P_{ilt} C_{pfi,lt}} = \frac{\left(\frac{P_{pfi,lt}}{\xi_{pfi,lt}}\right)^{1-\sigma_p}}{P_{pf,lt}^{1-\sigma_p}}.
$$

Consider the firm-level market share and take logs

$$
\begin{aligned}
\ln S_{pf,lt} &= (1-\eta_p)\ln P_{pf,lt} - (1-\eta_p)\ln P_{p,lt} + (\eta_p - 1)\ln \xi_{pf,lt} \\
\ln P_{p,lt} &= \ln P_{pf,lt} - \ln \xi_{pf,lt} + \frac{1}{\eta_p - 1}(\ln S_{pf,lt}) \\
&= \ln P_{pf,lt} - \ln \xi_{pf,lt} + \frac{1}{\eta_p - 1}\left(\ln S^{kl}_{pf,lt} + \ln \lambda^{kl}_{p,lt}\right).
\end{aligned}
$$

Take the difference between $\ln P_{p,kt}$ and $\ln P_{p,lt}$ and take an unweighted arithmetic average over the set of common firms ($f \in \Omega^{kl}_p$) and a cross-sectional difference across regions l and k at time t:

$$
\begin{aligned}
\frac{1}{N^{kl}_p}\sum_{f\in\Omega^{kl}_p}[\ln P_{p,kt} - \ln P_{plt}] &= \frac{1}{N^{kl}_p}\sum_{f\in\Omega^{kl}_p}\Bigg[(\ln P_{fp,kt} - \ln P_{pf,lt}) - (\ln \xi_{fp,kt} - \ln \xi_{fp,kt}) \\
&\qquad + \frac{1}{\eta_p - 1}\left(\ln S^{kl}_{fp,kt} - \ln S^{kl}_{fp,kt}\right) + \frac{1}{\eta_p - 1}\left(\ln \lambda^{kl}_{p,kt} - \ln \lambda^{kl}_{p,lt}\right)\Bigg] \\
\ln P_{p,kt} - \ln P_{p,lt} &= \frac{1}{N^{kl}_p}\sum_{f\in\Omega^{kl}_p}(\ln P_{fp,kt} - \ln P_{pf,lt}) + \frac{1}{\eta_p - 1}\frac{1}{N^{kl}_p}\sum_{f\Omega^{kl}_p}\left(\ln S^{kl}_{fp,kt} - \ln S^{kl}_{fp,kt}\right) \\
&\qquad + \frac{1}{\eta_p - 1}\left(\ln \lambda^{kl}_{p,kt} - \ln \lambda^{kl}_{p,lt}\right),
\end{aligned}
$$

where the second line uses the normalization that consumer tastes in region l and k for the set of firms that sell both to region l and k, are the same on average.

We provide some additional intuition into why the second correction term captures taste differences in addition to substitution effects. Starting with the substitution effect, in the presence of LOP deviations, consumers in different regions will have different expenditure shares on the same bundle. The substitution effect ensures that each firm-level price difference is weighted according to its welfare-relevant weight in the consumption baskets in both regions. In the knife-edge case where regional taste differences are zero, the second correction term would collapse to the well-known Sato-Vartia index.[45] To see why the second correction term also captures regional differences in consumer taste, suppose that there are no LOP deviations and that consumer tastes are more dispersed in region k relative to region l. Intuitively, such a difference in dispersion in consumer taste leads consumers in k to allocate a greater share of expenditure to firms for which they have a high taste. As they derive more utility from the consumption of high-taste bundles, their welfare is higher and this should also be reflected in a lower cost-of-living level. Mechanically, greater dispersion in consumer taste is accompanied by more dispersion in firm-level common market shares and this shows up in a lower geometric average of common market shares and a lower cost-of-living level. As a final point, in addition to the difference in common market share, the second correction term also depends on the firm-level elasticity of substitution. This is because the higher elasticity of substitution the more responsive are consumers to prices relative to tastes, which lowers the need to correct the price term.

Decomposing $P_{fp,kt} - P_{pf,lt}$ follows similar steps. Consider the variety-level market share and take logs

$$\begin{aligned}
\ln S_{pfi,lt} &= (1-\sigma_p)\ln P_{pfi,lt} - (1-\sigma_p)\ln P_{pf,lt} + (\sigma_p - 1)\ln \xi_{pfi,lt} \\
\ln P_{pf,lt} &= \ln P_{pfi,lt} - \ln \xi_{pfi,lt} + \frac{1}{\sigma_p - 1}\left(\ln S_{pfi,lt}\right) \\
&= \ln P_{pfi,lt} - \ln \xi_{pfi,lt} + \frac{1}{\sigma_p - 1}\left(\ln S^{kl}_{pfi,lt} + \ln \lambda^{kl}_{pf,lt}\right)
\end{aligned}$$

Take the difference between $\ln P_{fp,kt}$ and $\ln P_{pf,lt}$ and take an unweighted arithmetic average over the set of common varieties ($i \in \Omega^{kl}_{pf}$) and a cross-sectional difference across regions l and k at time t:

$$\begin{aligned}
\frac{1}{N^{kl}_{pf}} \sum_{i \in \Omega^{kl}_{pf}} \left[\ln P_{fp,kt} - \ln P_{plt}\right] = \frac{1}{N^{kl}_{pf}} \sum_{i \in \Omega^{kl}_{pf}} \Bigg[&\left(\ln P_{pfi,kt} - \ln P_{pfi,lt}\right) - \left(\ln \xi_{pfi,kt} - \ln \xi_{pfi,kt}\right) \\
&+ \frac{1}{\sigma_p - 1}\left(\ln S^{kl}_{pfi,kt} - \ln S^{kl}_{fp,kt}\right) + \frac{1}{\sigma_p - 1}\left(\ln \lambda^{kl}_{fp,kt} - \ln \lambda^{kl}_{pf,lt}\right) \Bigg] \\
\ln P_{fp,kt} - \ln P_{pf,lt} = \frac{1}{N^{kl}_{pf}} \sum_{i \in \Omega^{kl}_{pf}} &\left(\ln P_{pfi,kt} - \ln P_{pfi,lt}\right) + \frac{1}{\sigma_p - 1} \frac{1}{N^{kl}_{pf}} \sum_{i \in \Omega^{kl}_{pf}} \left(\ln S^{kl}_{pfi,kt} - \ln S^{kl}_{pfi,kt}\right) \\
&+ \frac{1}{\sigma_p - 1}\left(\ln \lambda^{kl}_{fp,kt} - \ln \lambda^{kl}_{pf,lt}\right)
\end{aligned}$$

[45] This follows immediately from the derivation of the common market share terms when setting $\xi_{pf,kt} = \xi_{pf,lt} \ \forall \ f \in \Omega^{kl}_p$ and $\xi_{pfi,kt} = \xi_{pfi,lt} \ \forall \ i \in \Omega^{kl}_p$.

, where we have used the normalization that consumer tastes in region l and k for the set of common varieties sold by firm f in region l and k, are the same on average. Then, we can plug this expression into the expression for $\ln P_{p,kt} - \ln P_{p,lt}$ to arrive at the final decomposition:

$$
\begin{aligned}
&\ln P_{p,kt} - \ln P_{p,lt} \\
&\quad = \frac{1}{N_p^{kl}} \sum_{f\in\Omega_p^{kl}} \left[\frac{1}{N_{pf}^{kl}} \sum_{i\in\Omega_{pf}^{kl}} \left(\ln P_{pfi,kt} - \ln P_{pfi,lt}\right) \right. \\
&\qquad \left. + \frac{1}{\sigma_p - 1} \frac{1}{N_{pf}^{kl}} \sum_{i\in\Omega_{pf}^{kl}} \left(\ln S_{pfi,kt}^{kl} - \ln S_{pfi,kt}^{kl}\right) + \frac{1}{\sigma_p - 1} \frac{1}{N_{pf}^{kl}} \sum_{i\in\Omega_{pf}^{kl}} \left(\ln \lambda_{fp,kt}^{kl} - \ln \lambda_{pf,lt}^{kl}\right) \right] \\
&\qquad + \frac{1}{\eta_p - 1} \frac{1}{N_p^{kl}} \sum_{f\Omega_p^{kl}} \left(\ln S_{fp,kt}^{kl} - \ln S_{fp,kt}^{kl}\right) + \frac{1}{\eta_p - 1} \left(\ln \lambda_{p,kt}^{kl} - \lambda_{p,lt}^{kl}\right) \\
&\quad = \frac{1}{N_p^{kl}} \sum_{f\in\Omega_p^{kl}} \left[\frac{1}{N_{pf}^{kl}} \sum_{i\in\Omega_{pf}^{kl}} \left(\ln P_{pfi,kt} - \ln P_{pfi,lt}\right) \right] \\
&\qquad + \frac{1}{N_p^{kl}} \sum_{f\in\Omega_p^{kl}} \left[\frac{1}{\eta_p - 1} \left(\ln S_{fp,kt}^{kl} - \ln S_{fp,kt}^{kl}\right) + \frac{1}{\sigma_p - 1} \frac{1}{N_{pf}^{kl}} \sum_{i\in\Omega_{pf}^{kl}} \left(\ln S_{fp,kt}^{kl} - \ln S_{fp,kt}^{kl}\right) \right] \\
&\qquad + \frac{1}{\eta_p - 1} \left(\ln \lambda_{p,kt}^{kl} - \ln \lambda_{p,lt}^{kl}\right) + \frac{1}{N_p^{kl}} \sum_{f\in\Omega_p^{kl}} \left[\frac{1}{\sigma_p - 1} \left(\ln \lambda_{fp,kt}^{kl} - \ln \lambda_{pf,lt}^{kl}\right) \right]
\end{aligned}
$$

To arrive at:

$$
\begin{aligned}
\ln P_{p,kt} - \ln P_{p,lt} = &\underbrace{\frac{1}{N_p^{kl}} \sum_{f\in\Omega_p^{kl}} \left[\frac{1}{N_{pf}^{kl}} \sum_{i\in\Omega_{pf}^{kl}} \left[\left(\ln MC_{pfi,kt} - \ln MC_{pfi,lt}\right) + \left(\ln \mathcal{M}_{pfi,kt} - \ln \mathcal{M}_{pfi,lt}\right)\right] \right]}_{\text{LOP deviations: Marginal cost + Markups}} \\
&+ \underbrace{\frac{1}{N_p^{kl}} \sum_{f\in\Omega_p^{kl}} \left[\frac{1}{\eta_p - 1} \left(\ln S_{fp,kt}^{kl} - \ln S_{fp,kt}^{kl}\right) + \frac{1}{\sigma_p - 1} \frac{1}{N_{pf}^{kl}} \sum_{i\in\Omega_{pf}^{kl}} \left(\ln S_{fp,kt}^{kl} - \ln S_{fp,kt}^{kl}\right) \right]}_{\text{Differences in Tastes}} \\
&+ \underbrace{\frac{1}{\eta_p - 1} \left(\ln \lambda_{p,kt}^{kl} - \ln \lambda_{p,lt}^{kl}\right) + \frac{1}{N_p^{kl}} \sum_{f\in\Omega_p^{kl}} \left[\frac{1}{\sigma_p - 1} \left(\ln \lambda_{fp,kt}^{kl} - \ln \lambda_{pf,lt}^{kl}\right) \right]}_{\text{Differences in Choice sets}}
\end{aligned}
$$

C.2 Proof of Proposition 1

C.2.1 Baseline case

Let production take place in location z and kl be a domestic region pair if $B^{kl} = 0$ and an international region pair if $B^{kl} = 1$.

Part 1 of Proposition 1 The first statement is the following:

$$\mathbb{E}\Big[\big|L^{kl}_{p,t}(1)\big| - \big|L^{kl}_{p,t}(0)\big| \,\Big|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\Big] > 0 \qquad \Longrightarrow \exists\ \tau_{pfi,t} > 1$$

First note that

$$\begin{aligned}
\big|L^{kl}_{p,t}\big| &= \Bigg| \sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t} \Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t} \left(\text{ln}P_{pfi,kt} - \text{ln}P_{pfi,lt}\right) \Big] \Bigg| \\
&= \Bigg| \sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t} \Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t} \left(\text{ln}\mathcal{M}_{pfi,kt} + \text{lnMC}_{pfi,kt} - \text{ln}\mathcal{M}_{pfi,lt} - \text{lnMC}_{pfi,lt}\right) \Big] \Bigg| \\
&= \Bigg| \sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t} \Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t} \left(\text{lnMC}_{pfi,kt} - \text{lnMC}_{pfi,lt}\right) \Big] \Bigg|,
\end{aligned}$$

where the first equality follows from (5), and the second and third equality use the optimal pricing rule under monopolistic competition with the nested CES demand system presented in the text. We can now write the following two expectations. First, we have

$$\begin{aligned}
&\mathbb{E}\Big[\big|L^{kl}_{p,t}(1)\big| \,\Big|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\Big] \\
&\quad = \mathbb{E}\Bigg[\Bigg| \sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t} \Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t} \left(\text{lnMC}_{pfi,kt}(1) - \text{lnMC}_{pfi,lt}(1)\right) \Big] \Bigg| \Bigg|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\Bigg] \\
&\quad = \mathbb{E}\Bigg[\Bigg| \sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t} \Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t} \Big(\text{ln}\varphi_{pfi,zt} + \text{ln}t_{pfi,zt}\left(\boldsymbol{X}^{kz}\right) + \text{ln}\left(\tau_{pfi,t}\right) \\
&\qquad\qquad - \text{ln}\varphi_{pfi,zt} - \text{ln}t_{pfi,zt}\left(\boldsymbol{X}^{lz}\right)\Big) \Big] \Bigg| \Bigg|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\Bigg] \\
&\quad = \mathbb{E}\Bigg[\Bigg| \sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t} \Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t} \sum_{i\in\Omega^{kl}_p} \Big(\text{ln}t_{pfi,zt}\left(\boldsymbol{X}^{kz}\right) + \text{ln}\left(\tau_{pfi,t}\right) - \text{ln}t_{pfi,zt}\left(\boldsymbol{X}^{lz}\right)\Big) \Big] \Bigg| \Bigg|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\Bigg] \\
&\quad = \mathbb{E}\Bigg[\Bigg| \sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t} \Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t} \text{ln}\tau_{pfi,t} \Big] \Bigg| \Bigg|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\Bigg],
\end{aligned}$$

where the second equality uses the expression of the marginal cost function and the fact that k and l are an international region pair ($B^{kl} = 1$), and the fourth equality uses the conditioning on geographic differences $\boldsymbol{X}^{zk} = \boldsymbol{X}^{zl}$ whenever $\boldsymbol{X}^{kl} = 0$. Second, we have

$$\begin{aligned}
&\mathbb{E}\Big[\,\big|L^{kl}_{p,t}(0)\big|\,\Big|\boldsymbol{X}^{kl}=0, B^{kl}=1\Big] \\
&\qquad= \mathbb{E}\left[\Big|\sum_{f\in\Omega^{kl}_p}\omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p}\omega^{kl}_{pfi,t}\left(\text{lnMC}_{pfi,kt}(0)-\text{lnMC}_{pfi,lt}(0)\right)\Big]\Big|\,\Big|\boldsymbol{X}^{kl}=0, B^{kl}=1\right] \\
&\qquad= \mathbb{E}\left[\Big|\sum_{f\in\Omega^{kl}_p}\omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p}\omega^{kl}_{pfi,t}\big(\ln\varphi_{pfi,zt}+\ln t_{pfi,zt}\left(\boldsymbol{X}^{kz}\right)-\ln\varphi_{pfi,zt}-\ln t_{pfi,zt}\left(\boldsymbol{X}^{lz}\right)\big)\Big]\Big|\,\Big|\boldsymbol{X}^{kl}=0, B^{kl}=1\right] \\
&\qquad= \mathbb{E}\left[\Big|\sum_{f\in\Omega^{kl}_p}\omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p}\omega^{kl}_{pfi,t}\big(\ln t\left(\boldsymbol{X}^{kz}\right)-\ln t\left(\boldsymbol{X}^{lz}\right)\big)\Big]\Big|\,\Big|\boldsymbol{X}^{kl}=0, B^{lk}=1\right] \\
&\qquad= 0
\end{aligned}$$

where the second equality now uses the fact that consumption is domestic at both k and l and the fourth equality again uses that $\boldsymbol{X}^{kz} = \boldsymbol{X}^{lz}$ whenever $\boldsymbol{X}^{kl} = 0$. Subtracting both expectations, we obtain:

$$\mathbb{E}\Big[\,\big|L^{kl}_{p,t}(1)\big|-\big|L^{kl}_{p,t}(0)\big|\,\Big|\boldsymbol{X}^{kl}=0, B^{kl}=1\Big] = \mathbb{E}\left[\Big|\sum_{f\in\Omega^{kl}_p}\omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p}\omega^{kl}_{pfi,t}\ln\tau_{pfi,t}\Big]\Big|\,\Big|\boldsymbol{X}^{kl}=0, B^{kl}=1\right]$$

which is different from zero only if there exists an $\tau_{pfi,t}$ that is greater than one.

Part 2 of Proposition 1 The second statement is the following:

$$\mathbb{E}\Big[\,\big|\Lambda^{kl}_{p,t}(1)\big|-\big|\Lambda^{kl}_{p,t}(0)\big|\,\Big|\boldsymbol{X}^{kl}=0, B^{kl}=1\Big] > 0 \qquad \Longrightarrow \exists\; F^{X}_{pf,t} > 0$$

For simplicity, we will focus on the firm-level product availability differences between regions k and l, which is defined in the text as $\Lambda^{kl}_{p,t} \equiv \frac{1}{\eta_p-1}\left(\ln\lambda^{kl}_{p,kt}-\ln\lambda^{kl}_{p,kt}\right)$. The argument for variety-level differences (according to the definition of $\Lambda^{kl}_{p,t}$ in the text) is analogous, but slightly more tedious. Recall from the text that

$$\lambda^{kl}_{p,lt} \equiv \frac{\sum_{i\in\Omega^{kl}_p}P_{pf,lt}Q_{pf,lt}}{\sum_{i\in\Omega_{p,lt}}P_{pf,lt}Q_{pf,lt}}$$

is the expenditure share spent in region l on varieties that are common to regions k and l. For the first expectation, we have

$$\begin{aligned}
&\mathbb{E}\Big[\,\big|\Lambda^{kl}_{p,t}(1)\big|\,\Big|\boldsymbol{X}^{kl}=0, B^{kl}=1\Big] \\
&\qquad= \mathbb{E}\left[\left|\frac{1}{\eta_p-1}\left(\ln\lambda^{kl}_{p,kt}(1)-\ln\lambda^{kl}_{p,lt}(1)\right)\right|\,\middle|\boldsymbol{X}^{kl}=0, B^{kl}=1\right] \\
&\qquad= \mathbb{E}\left[\left|\frac{1}{\eta_p-1}\left(\ln\lambda^{kl}_{p,kt}-\ln\lambda^{kl}_{p,lt}\right)\right|\,\middle|\boldsymbol{X}^{kl}=0, B^{kl}=1\right],
\end{aligned}$$

where the second equality follows from the fact that k and l are an international region pair ($B^{kl}=1$). For the second expectation, we have

$$\begin{aligned}
&\mathbb{E}\Big[\,\big|\Lambda^{kl}_{p,t}(0)\big|\,\Big|\boldsymbol{X}^{kl}=0,B^{kl}=1\Big]\\
&\qquad=\mathbb{E}\left[\,\left|\frac{1}{\eta_p-1}\left(\ln\lambda^{kl}_{p,kt}(0)-\ln\lambda^{kl}_{p,lt}(0)\right)\right|\,\middle|\boldsymbol{X}^{kl}=0,B^{kl}=1\right]\\
&\qquad=0,
\end{aligned}$$

where the second equality uses the fact that $\lambda^{kl}_{p,kt}(0)=\lambda^{kl}_{p,lt}(0)=1$ because $\Omega_{p,lt}=\Omega^{lk}_{p}$ when k and l form a domestic region pair.

Subtracting both expectations, we obtain:

$$\begin{aligned}
&\mathbb{E}\Big[\,\big|\Lambda^{kl}_{p,t}(1)\big|-\big|\Lambda^{kl}_{p,t}\big|\,\Big|\boldsymbol{X}^{kl}=0,B^{kl}=1\Big]\\
&\qquad=\mathbb{E}\left[\,\left|\frac{1}{\eta_p-1}\left(\ln\lambda^{kl}_{p,kt}-\ln\lambda^{kl}_{p,lt}\right)\right|\,\middle|\boldsymbol{X}^{kl}=0,B^{kl}=1\right]
\end{aligned}$$

By the CES demand system, if $F^{X}_{pf,t}=0$, then $\Omega_{p,kt}=\Omega_{p,lt}=\Omega^{kl}_{p}$, so that $\lambda^{kl}_{p,kt}=\lambda^{kl}_{p,lt}=1$. Therefore, if the expression is different zero, it implies that $F^{X}_{pf,t}>0$.

C.2.2 Extensions

Oligopolistic competition Assuming oligopolistic competition instead of monopolistic competition has the following implications. Given that the second part of Proposition 1 does not rely on the markup rule, assuming oligopolistic competition instead of monopolistic does not impact the proof of this part. However, in the first part of the proposition, markups do not necessarily difference out. Nevertheless, we can still decompose final consumer prices into a markup component and a marginal cost component:

$$\begin{aligned}
L^{kl}_{p,t}&=\sum_{f\in\Omega^{kl}_{p}}\omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_{p}}\omega^{kl}_{pfi,t}\left(\ln P_{pfi,kt}-\ln P_{pfi,lt}\right)\Big]\\
&=\sum_{f\in\Omega^{kl}_{p}}\omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_{p}}\omega^{kl}_{pfi,t}\left(\ln\mathcal{M}_{pfi,kt}+\ln\mathrm{MC}_{pfi,kt}-\ln\mathcal{M}_{pfi,lt}-\ln\mathrm{MC}_{pfi,lt}\right)\Big]\\
&=\sum_{f\in\Omega^{kl}_{p}}\omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_{p}}\omega^{kl}_{pfi,t}\left(\ln\mathrm{MC}_{pfi,kt}-\ln\mathrm{MC}_{pfi,lt}\right)\Big]\\
&\qquad+\sum_{f\in\Omega^{kl}_{p}}\omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_{p}}\omega^{kl}_{pfi,t}\left(\ln\mathcal{M}_{pfi,kt}-\ln\mathcal{M}_{pfi,kt}\right)\Big]
\end{aligned}$$

To detect whether there exist positive variable costs, we can apply the same arguments as before and consider the following test instead:

$$\mathbb{E}\Big[\,\big|\text{MC}^{kl}_{p,t}(1)\big| - \big|\text{MC}^{kl}_{p,t}(0)\big|\,\Big|\boldsymbol{X}^{kl}=0, B^{kl}=1\Big] > 0 \qquad \Longrightarrow \exists\, \tau_{pfi,t} > 1$$

where $\text{MC}^{kl}_{p,t} \equiv \sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\left(\text{lnMC}_{pfi,kt} - \text{lnMC}_{pfi,lt}\right)\Big]$.

General variable trade costs Consider a more general expression for the marginal cost:

$$\text{MC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{lz}\right), \tau_{pfi,t}B^{zl}\right)$$

Given that the second part of Proposition 1 only relies on the CES-assumption, allowing for more general variable marginal costs does not impact the proof of this part. However, in the first part of the proposition, the expression slightly changes:

$$\begin{aligned}
\left|L^{kl}_{p,t}\right| &= \left|\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\left(\text{ln}P_{pfi,kt} - \text{ln}P_{pfi,lt}\right)\Big]\right| \\
&= \left|\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\left(\text{ln}\mathcal{M}_{pfi,kt} + \text{lnMC}_{pfi,kt} - \text{ln}\mathcal{M}_{pfi,lt} - \text{lnMC}_{pfi,lt}\right)\Big]\right| \\
&= \left|\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\left(\text{lnMC}_{pfi,kt} - \text{lnMC}_{pfi,lt}\right)\Big]\right|,
\end{aligned}$$

where the first equality follows from (5), and the second and third equality use the optimal pricing rule under monopolistic competition with the nested CES demand system presented in the text. We can now write the following two expectations. First, we have

$$\begin{aligned}
&\mathbb{E}\Big[\,\big|L^{kl}_{p,t}(1)\big|\,\Big|\boldsymbol{X}^{kl}=0, B^{kl}=1\Big] \\
&\quad= \mathbb{E}\left[\left|\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\left(\text{lnMC}_{pfi,kt}(1) - \text{lnMC}_{pfi,lt}(1)\right)\Big]\right|\,\middle|\boldsymbol{X}^{kl}=0, B^{kl}=1\right] \\
&\quad= \mathbb{E}\Bigg[\Bigg|\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\Big(\text{lnMC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{kz}\right), \tau_{pfi,t}B^{zk}\right) - \\
&\qquad\qquad \text{lnMC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{lz}\right), 0\right)\Big)\Big]\Bigg|\,\Bigg|\boldsymbol{X}^{kl}=0, B^{kl}=1\Bigg] \\
&\quad= \mathbb{E}\Bigg[\Bigg|\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\Big(\text{lnMC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{lz}\right), \tau_{pfi,t}\right) - \\
&\qquad\qquad \text{lnMC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{lz}\right), 0\right)\Big)\Big]\Bigg|\,\Bigg|\boldsymbol{X}^{kl}=0, B^{kl}=1,\Bigg]
\end{aligned}$$

where the second equality uses the expression of the marginal cost function and the assumption that production takes place at z and consumption at k is foreign whereas consumption at l is domestic, and the fourth equality uses the conditioning on geographic differences $\boldsymbol{X}^{zk} = \boldsymbol{X}^{zl}$ whenever $\boldsymbol{X}^{kl} = 0$. Second, we have

$$\begin{aligned}
&\mathbb{E}\Big[\,\big|L^{kl}_{p,t}(1)\big|\,\Big|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\Big] \\
&\quad = \mathbb{E}\left[\left|\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\left(\ln\text{MC}_{pfi,kt}(1) - \ln\text{MC}_{pfi,lt}(1)\right)\Big]\right|\middle|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\right] \\
&\quad = \mathbb{E}\Bigg[\Bigg|\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\Big(\ln\text{MC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{kz}\right), \tau_{pfi,t}B^{kz}\right) - \\
&\qquad\qquad \ln\text{MC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{lz}\right), 0\right)\Big)\Big]\Bigg|\,\Bigg|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\Bigg] \\
&\quad = \mathbb{E}\Bigg[\Bigg|\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\Big(\ln\text{MC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{lz}\right), 0\right) - \\
&\qquad\qquad \ln\text{MC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{lz}\right), 0\right)\Big)\Big]\Bigg|\,\Bigg|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\Bigg] \\
&\quad = 0
\end{aligned}$$

where the second equality now uses the fact that consumption is domestic at both k and l and the fourth equality again uses that $\boldsymbol{X}^{kz} = \boldsymbol{X}^{lz}$ whenever $\boldsymbol{X}^{kl} = 0$. Subtracting both expectations, we obtain:

$$\begin{aligned}
&\mathbb{E}\Big[\,\big|L^{kl}_{p,t}(1)\big| - \big|L^{kl}_{p,t}(0)\big|\,\Big|\boldsymbol{X}^{kl} = 0, B^{kl} = 1\Big] \\
&\quad = \mathbb{E}\Bigg[\Bigg|\sum_{f\in\Omega^{kl}_p} \omega^{kl}_{pf,t}\Big[\sum_{i\in\Omega^{kl}_p} \omega^{kl}_{pfi,t}\Big(\ln\text{MC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{lz}\right), \tau_{pfi,t}\right) - \\
&\qquad\qquad \ln\text{MC}\left(\varphi_{pfi,zt}, t\left(\boldsymbol{X}^{lz}\right), 0\right)\Big)\Big]\Bigg|\,\Bigg|B^{kl} = 1\Bigg]
\end{aligned}$$

which is only different from zero if there exists an $\tau_{pfi,t}$ that is greater than one.

D Structural estimation

D.1 Barcode-level Elasticities

D.1.1 Estimation details

Objective function In the estimation, we rely on the following moment condition $\mathbb{E}_t\left[\varepsilon_{icl,t}|\bar{p}_{ic-l,t},\boldsymbol{\theta},\boldsymbol{\lambda}\right]=0$ and minimize the following GMM-objective function to obtain:

$$\widehat{\sigma_p}=\arg\min_{\sigma_p}\boldsymbol{M}(\sigma_p)'\boldsymbol{W}\boldsymbol{M}(\sigma_p)\qquad\forall p\in\mathcal{P}$$

where

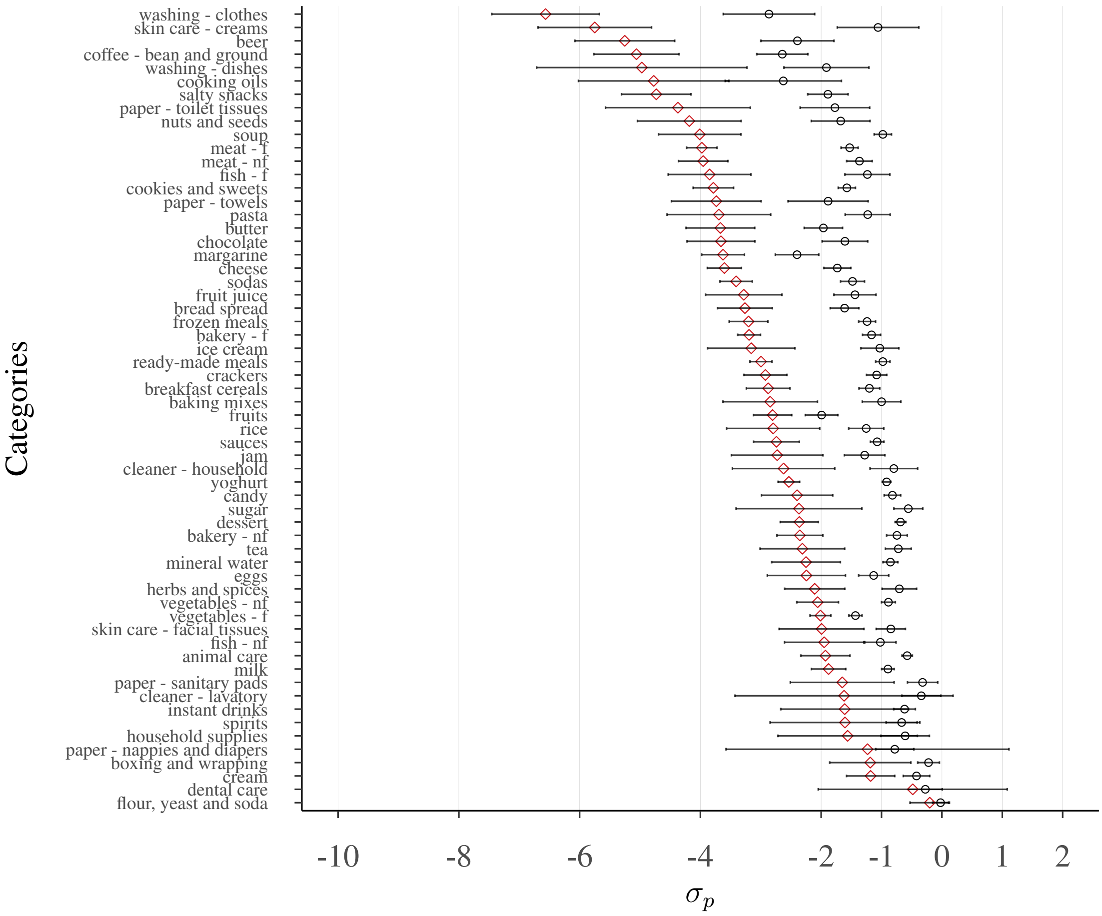
$$M_{icl}(\sigma_p)=\mathbb{E}_t\left[\bar{p}_{ic-l,t}\varepsilon_{icl,t}(\sigma_p)\right],\qquad\bar{p}_{ic-l,t}\equiv\frac{1}{N_{lc}}\sum_{k\in\mathcal{L}_c\setminus l}p_{ick,t}$$

and $\boldsymbol{W}$ is a weighting matrix that weights the variety-region moment conditions using the number of transactions associated with that variety in that region. For this reason, our estimator is very similar to the one developed in Dellavigna & Gentzkow (2019) but different from Faber & Fally (2021) which estimates brand-level elasticities in the US using only regional variation and no variation across retail chains and different from Atkin et al. (2018) which use it to estimate store-level elasticities in Mexico by collapsing the variety dimension.

Frequency restrictions on the sample We place restrictions on the frequency in which varieties are sold because there is widespread evidence of the existence of many zeros in scanner data which might potentially downwardly bias the elasticity estimates (e.g. Dubé et al. (2021); Gandhi et al. (2022)). Given our broad focus on many categories, it is hard to obtain exogenous variation in choice set determination for each category as in Dubé et al. (2021). Instead, we choose to only include varieties that are frequently purchased and thus suffer less from zero market shares. Below, we discuss the sensitivity of the estimates to alternative sample restrictions.

D.1.2 Estimation results

Figure D.1: Elasticity of substitution σ_p: Weekly frequency $\sum_{t \in y(t)} \mathbb{1}(P_{il,t} C_{il,t} > 0) \geq 0.5$



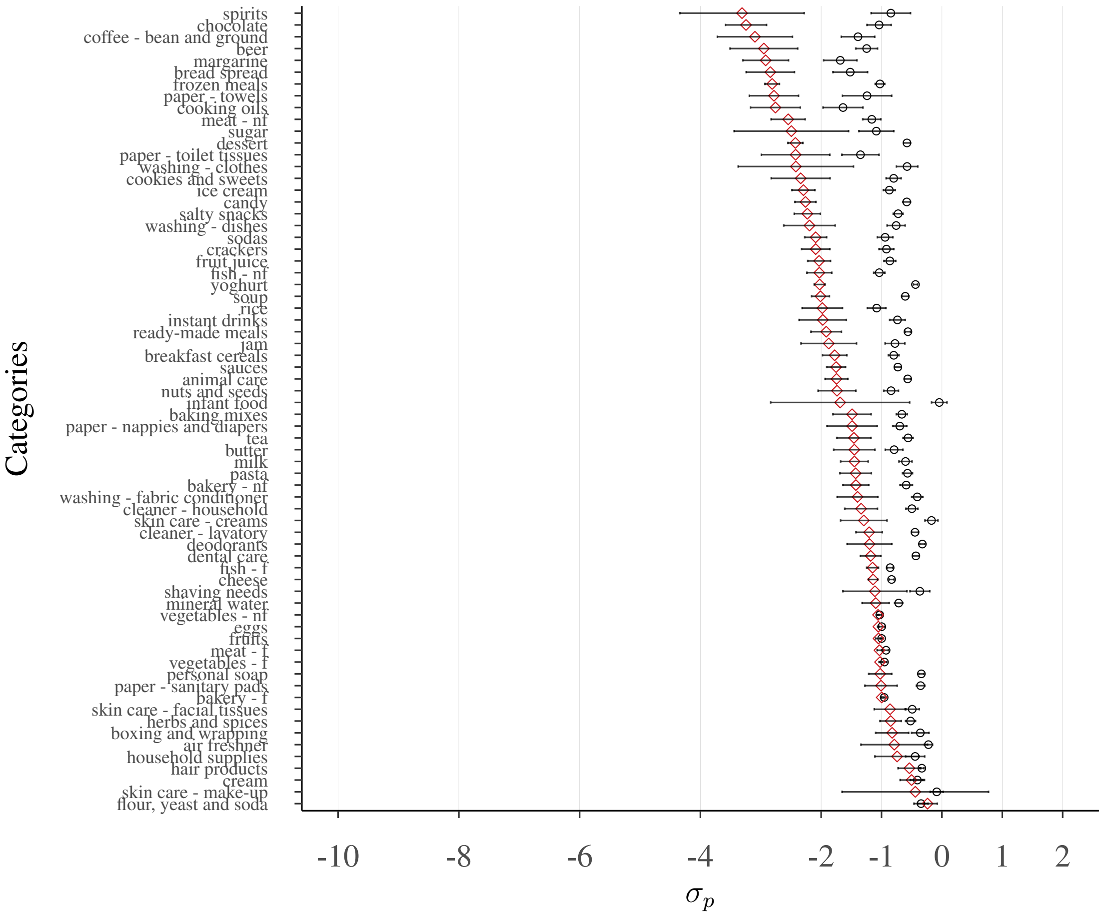
Notes: This figure shows the OLS and IV-estimates of the variety level elasticities of substitution σ_p estimated using consumption data at the weekly frequency. The estimations include all variety-region-week observations for which weekly sales are positive in over 50% of weeks in a given year. We include variety-region-chain-year FEs, variety-region-chain-week and category-region-chain-week FEs. Alongside the parameters, we plot 95% confidence intervals based on clustered standard errors at the variety level. For expositional purposes, we omit estimates for which the confidence intervals are outside of the $[-10, 2]$ range.

Table D.1: Weekly Barcode-level Elasticities: Within store instrument

			Unweighted			Weighted			OLS			IV		
Sample	Specification	nr. Cat	$\hat{\beta}_{\text{IV}} \neq 0$	$\hat{\beta}_{\text{IV}} \neq -1$	$\hat{\beta}_{\text{IV}} > -1$	$\hat{\beta}_{\text{IV}} \neq 0$	$\hat{\beta}_{\text{IV}} \neq -1$	$\hat{\beta}_{\text{IV}} > -1$	p10	p50	p90	p10	p50	p90
Full sample	i-n-c-y + i-n-c-w + p-n-c-t	68	0.84	0.72	0.18	0.74	0.69	0.12	-1.52	-0.81	-0.25	-7.18	-2.34	0.39
Full sample	i-n-c-y + i-n-c-w + p-n-f-t	68	0.69	0.54	0.26	0.83	0.58	0.29	-1.50	-0.78	-0.25	-5.91	-2.32	1.80
Full sample	i-n-c-y + i-n-c-w + p-n-c-f-t	68	0.47	0.19	0.59	0.46	0.22	0.56	-1.24	-0.61	-0.23	-5.30	0.04	7.28
Full sample	i-n-c-y + i-n-c-w + p-r-c-t	68	0.88	0.75	0.09	0.93	0.73	0.08	-1.30	-0.57	-0.20	-4.06	-2.03	0.79
Full sample	i-n-c-y + i-n-c-w + p-r-f-t	68	0.85	0.75	0.07	0.91	0.86	0.02	-1.30	-0.56	-0.21	-3.76	-1.93	0.39
Full sample	i-n-c-y + i-n-c-w + p-r-c-f-t	68	0.87	0.69	0.09	0.96	0.88	0.03	-1.04	-0.45	-0.18	-3.45	-1.74	0.52
T $\geq$ 25%	i-n-c-y + i-n-c-w + p-n-c-t	68	0.82	0.78	0.07	0.88	0.87	0.03	-1.79	-1.05	-0.35	-5.99	-3.43	0.07
T $\geq$ 25%	i-n-c-y + i-n-c-w + p-n-f-t	68	0.76	0.71	0.13	0.89	0.82	0.11	-1.70	-0.99	-0.34	-7.49	-3.49	1.45
T $\geq$ 25%	i-n-c-y + i-n-c-w + p-n-c-f-t	68	0.57	0.49	0.24	0.70	0.53	0.31	-1.34	-0.75	-0.27	-11.13	-3.65	2.88
T $\geq$ 25%	i-n-c-y + i-n-c-w + p-r-c-t	68	0.88	0.84	0.00	0.95	0.94	0.00	-1.82	-1.05	-0.42	-4.75	-2.98	-1.10
T $\geq$ 25%	i-n-c-y + i-n-c-w + p-r-f-t	68	0.90	0.82	0.01	0.96	0.95	0.00	-1.76	-1.01	-0.44	-4.21	-2.78	-0.88
T $\geq$ 25%	i-n-c-y + i-n-c-w + p-r-c-f-t	68	0.91	0.79	0.04	0.97	0.94	0.01	-1.55	-0.82	-0.33	-3.72	-2.33	-0.81
T $\geq$ 50%	i-n-c-y + i-n-c-w + p-n-c-t	68	0.81	0.72	0.04	0.87	0.84	0.02	-2.35	-1.20	-0.22	-7.18	-3.88	1.02
T $\geq$ 50%	i-n-c-y + i-n-c-w + p-n-f-t	68	0.75	0.66	0.12	0.85	0.77	0.09	-2.34	-1.13	-0.28	-7.67	-4.17	1.85
T $\geq$ 50%	i-n-c-y + i-n-c-w + p-n-c-f-t	68	0.62	0.50	0.16	0.69	0.51	0.24	-1.66	-0.89	-0.17	-8.89	-3.83	4.20
T $\geq$ 50%	i-n-c-y + i-n-c-w + p-r-c-t	66	0.90	0.78	0.03	0.96	0.91	0.01	-2.30	-1.32	-0.22	-4.85	-3.46	-0.94
T $\geq$ 50%	i-n-c-y + i-n-c-w + p-r-f-t	66	0.85	0.78	0.03	0.95	0.92	0.01	-2.28	-1.21	-0.22	-5.01	-3.12	-1.15
T $\geq$ 50%	i-n-c-y + i-n-c-w + p-r-c-f-t	66	0.84	0.74	0.03	0.95	0.90	0.01	-1.96	-1.02	-0.22	-4.77	-2.77	-1.15
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-n-c-t	68	0.82	0.75	0.09	0.88	0.84	0.04	-1.96	-1.13	-0.31	-6.29	-3.41	-0.01
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-n-f-t	68	0.74	0.68	0.15	0.85	0.79	0.11	-1.94	-1.05	-0.32	-7.25	-3.52	1.32
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-n-c-f-t	68	0.56	0.43	0.24	0.68	0.44	0.29	-1.58	-0.80	-0.27	-8.13	-2.76	4.26
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-r-c-t	68	0.90	0.81	0.04	0.91	0.89	0.02	-2.00	-1.16	-0.42	-4.79	-2.97	-1.11
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-r-f-t	68	0.88	0.79	0.01	0.91	0.89	0.00	-2.02	-1.12	-0.43	-4.76	-2.86	-0.75
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-r-c-f-t	68	0.91	0.79	0.04	0.97	0.94	0.01	-1.95	-0.92	-0.37	-4.28	-2.54	-0.96
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-n-c-t	67	0.75	0.69	0.04	0.82	0.79	0.02	-2.35	-1.20	-0.20	-6.68	-3.89	1.04
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-n-f-t	67	0.72	0.66	0.10	0.83	0.76	0.09	-2.42	-1.15	-0.15	-7.32	-4.02	1.89
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-n-c-f-t	67	0.54	0.50	0.15	0.51	0.49	0.24	-1.84	-0.89	-0.17	-9.24	-3.88	3.23
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-r-c-t	66	0.88	0.76	0.04	0.91	0.87	0.02	-2.47	-1.35	-0.21	-5.20	-3.39	-1.11
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-r-f-t	66	0.87	0.76	0.04	0.91	0.87	0.01	-2.50	-1.28	-0.18	-5.14	-3.18	-1.31
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-w + p-r-c-f-t	66	0.85	0.74	0.04	0.95	0.90	0.01	-2.43	-1.05	-0.27	-5.12	-2.78	-1.05

Notes: This table provides an overview of the OLS and IV-estimates of the variety level elasticities of substitution σ_p estimated using consumption data at the weekly frequency for different specifications. The sample column indicates which restriction we place on the included sample. The specification columns indicate which sets of fixed effects we include. The nr. Cat shows how many categories the minimization routine for the IV-estimator converged successfully. The unweighted columns plot the fraction of IV estimates which are significantly different from 0, different from -1 and whether any estimates are statistically significantly larger than -1. The weighted column computes weighted shares by weighting each category at its expenditure share. Finally, the OLS and IV columns provide the distribution of OLS and IV estimates across categories respectively. All statistical tests are based on standard errors that are clustered at the variety level.

Figure D.2: Elasticity of substitution σ_p: Monthly frequency $\sum_{t\in y(t)} \mathbb{1}(P_{il,t}C_{il,t} > 0) \geq 0.5$



Notes: This figure shows the OLS and IV-estimates of the variety level elasticities of substitution σ_p estimated using consumption data at the monthly frequency. The estimations include all variety-region-month observations for which weekly sales are positive in over 50% of weeks in a given year. We include variety-region-chain-year FEs, variety-region-chain-month and category-region-chain-month FEs. Alongside the parameters, we plot 95% confidence intervals based on clustered standard errors at the variety level. We omit estimates for which the confidence intervals are outside of the $[-10, 2]$ range.

Table D.2: Monthly Barcode-level Elasticities: Within store instrument

			Unweighted			Weighted			OLS			IV		
Sample	Specification	nr. Cat	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	p10	p50	p90	p10	p50	p90
Full sample	i-n-c-y + i-n-c-m + p-n-c-t	29	0.37	0.25	0.04	0.37	0.24	0.05	-1.04	-0.61	-0.21	-3.61	-1.37	-0.16
Full sample	i-n-c-y + i-n-c-m + p-n-f-t	29	0.32	0.26	0.09	0.29	0.27	0.06	-1.06	-0.59	-0.20	-3.70	-1.83	1.62
Full sample	i-n-c-y + i-n-c-m + p-n-c-f-t	29	0.24	0.15	0.15	0.25	0.16	0.13	-0.88	-0.47	-0.14	-4.56	-0.78	8.05
Full sample	i-n-c-y + i-n-c-m + p-r-c-t	29	0.40	0.24	0.09	0.40	0.23	0.07	-1.01	-0.43	-0.10	-3.08	-1.41	-0.43
Full sample	i-n-c-y + i-n-c-m + p-r-f-t	29	0.37	0.26	0.06	0.37	0.30	0.02	-0.93	-0.38	-0.10	-3.53	-1.61	-0.19
Full sample	i-n-c-y + i-n-c-m + p-r-c-f-t	29	0.38	0.21	0.12	0.40	0.30	0.03	-0.71	-0.31	-0.06	-2.60	-1.32	0.02
T $\geq$ 25%	i-n-c-y + i-n-c-m + p-n-c-t	68	0.93	0.75	0.06	0.98	0.65	0.02	-1.01	-0.60	-0.26	-2.81	-1.80	-0.76
T $\geq$ 25%	i-n-c-y + i-n-c-m + p-n-f-t	68	0.93	0.82	0.03	0.93	0.90	0.01	-1.05	-0.56	-0.29	-3.59	-2.32	-1.18
T $\geq$ 25%	i-n-c-y + i-n-c-m + p-n-c-f-t	68	0.76	0.63	0.09	0.84	0.79	0.08	-0.89	-0.44	-0.21	-4.38	-2.71	2.87
T $\geq$ 25%	i-n-c-y + i-n-c-m + p-r-c-t	68	0.97	0.71	0.10	0.99	0.64	0.02	-1.01	-0.61	-0.28	-2.53	-1.64	-0.78
T $\geq$ 25%	i-n-c-y + i-n-c-m + p-r-f-t	68	0.99	0.71	0.09	1.00	0.65	0.02	-1.01	-0.60	-0.28	-2.70	-1.69	-0.86
T $\geq$ 25%	i-n-c-y + i-n-c-m + p-r-c-f-t	68	0.99	0.65	0.13	1.00	0.69	0.04	-0.98	-0.52	-0.27	-2.44	-1.48	-0.60
T $\geq$ 50%	i-n-c-y + i-n-c-m + p-n-c-t	68	0.96	0.79	0.01	0.98	0.67	0.00	-1.34	-0.82	-0.40	-3.09	-2.08	-0.99
T $\geq$ 50%	i-n-c-y + i-n-c-m + p-n-f-t	68	0.93	0.84	0.03	0.94	0.91	0.01	-1.48	-0.84	-0.42	-3.66	-2.54	-1.13
T $\geq$ 50%	i-n-c-y + i-n-c-m + p-n-c-f-t	68	0.81	0.68	0.07	0.86	0.80	0.02	-1.26	-0.65	-0.34	-4.34	-2.75	0.14
T $\geq$ 50%	i-n-c-y + i-n-c-m + p-r-c-t	68	0.97	0.76	0.01	0.99	0.66	0.00	-1.34	-0.85	-0.41	-2.92	-1.92	-1.00
T $\geq$ 50%	i-n-c-y + i-n-c-m + p-r-f-t	68	0.97	0.74	0.01	0.99	0.67	0.00	-1.34	-0.84	-0.40	-3.00	-1.89	-1.00
T $\geq$ 50%	i-n-c-y + i-n-c-m + p-r-c-f-t	68	0.99	0.72	0.04	1.00	0.72	0.02	-1.24	-0.73	-0.34	-2.81	-1.59	-0.82
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-n-c-t	68	0.93	0.78	0.04	0.98	0.68	0.01	-1.24	-0.72	-0.31	-3.04	-2.07	-0.93
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-n-f-t	68	0.94	0.84	0.01	0.98	0.94	0.00	-1.49	-0.73	-0.34	-3.73	-2.57	-1.32
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-n-c-f-t	68	0.75	0.60	0.12	0.88	0.80	0.06	-1.13	-0.54	-0.27	-4.44	-2.76	2.94
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-r-c-t	68	0.94	0.75	0.06	0.98	0.67	0.01	-1.30	-0.73	-0.34	-2.95	-1.87	-1.00
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-r-f-t	68	0.97	0.74	0.06	0.99	0.66	0.01	-1.26	-0.73	-0.32	-2.96	-1.83	-1.00
T $\geq$ 25% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-r-c-f-t	68	0.96	0.68	0.10	0.98	0.65	0.07	-1.14	-0.64	-0.29	-2.73	-1.58	-0.61
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-n-c-t	68	0.96	0.79	0.04	0.98	0.69	0.06	-1.51	-0.92	-0.45	-3.49	-2.31	-0.94
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-n-f-t	68	0.91	0.84	0.03	0.97	0.95	0.01	-1.94	-0.94	-0.48	-3.90	-2.86	-1.08
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-n-c-f-t	68	0.74	0.65	0.09	0.87	0.84	0.03	-1.60	-0.72	-0.36	-8.15	-3.21	0.02
= T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-r-c-t	68	0.96	0.81	0.03	0.98	0.69	0.01	-1.57	-0.92	-0.46	-3.03	-2.07	-0.87
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-r-f-t	68	0.96	0.75	0.01	0.98	0.67	0.00	-1.51	-0.91	-0.47	-3.14	-2.10	-0.86
T $\geq$ 50% & M $\geq$ 0.1%	i-n-c-y + i-n-c-m + p-r-c-f-t	68	0.96	0.69	0.07	0.98	0.66	0.07	-1.32	-0.79	-0.37	-2.98	-1.77	-0.80

Notes: This table provides an overview of the OLS and IV-estimates of the variety level elasticities of substitution σ_p estimated using consumption data at the monthly frequency for different specifications. The sample column indicates which restriction we place on the included sample. The specification columns indicate which sets of fixed effects we include. The nr. Cat shows how many categories the minimization routine for the IV-estimator converged successfully. The unweighted columns plot the fraction of IV estimates which are significantly different from 0, different from -1 and whether any estimates are statistically significantly larger than -1. The weighted column computes weighted shares by weighting each category at its expenditure share. Finally, the OLS and IV columns provide the distribution of OLS and IV estimates across categories respectively. All statistical tests are based on standard errors that are clustered at the variety level.

D.2 Firm-level Elasticities

D.2.1 Estimation details

Constructing the price and quantity indices Given our normalization, we back out the variety-level taste parameters by taking the ratio of the market share $S_{il,t}$ and its geometric average $\tilde{S}_{fpclt}$:

$$\frac{S^f_{il,t}}{\tilde{S}^f_{fpl,t}} = \frac{\left(\frac{P_{ilt}}{\varphi_{il,t}}\right)^{1-\sigma_p}}{\left(\prod_{i\in\mathcal{B}_{fpl,t}}\left(\frac{P_{il,t}}{\varphi_{il,t}}\right)^{1-\sigma_p}\right)^{\frac{1}{N_{fpl,t}}}}$$

$$= \frac{\left(\frac{P_{il,t}}{\varphi_{il,t}}\right)^{1-\sigma_p}}{\left(\frac{\tilde{P}_{fpl,t}}{\tilde{\varphi}_{fpl,t}}\right)^{1-\sigma_p}}$$

$$\varphi_{il,t} = \frac{P_{il,t}}{\tilde{P}_{fpl,t}}\left(\frac{S_{il,t}}{\tilde{S}_{fpl,t}}\right)^{\frac{1}{\sigma_p-1}}\tilde{\varphi}_{fpl,t}$$

where $\tilde{\varphi}_{fpl,t}$ is defined as before and $\tilde{P}_{fpl,t} \equiv \left(\prod_{i\in\mathcal{B}_{fpl,t}} P_{il,t}\right)^{\frac{1}{N_{fpl,t}}}$. Combined with the estimated elasticities of substitution, these backed-out demand residuals can be used to construct the quantity and price indices.

Structural instrument In addition, we can write the overall price index as the product of the unweighted geometric average firm-level price index and a term that depends on the dispersion in market share within firm

$$P_{fpl,t} = \left(\sum_{i\in\mathcal{B}_{fpl,t}} P^{1-\sigma_p}_{il,t}\varphi^{\sigma_p-1}_{il,t}\right)^{\frac{1}{1-\sigma_p}}$$

$$= \left(\sum_{i\in\mathcal{B}_{fpl,t}} P^{1-\sigma_p}_{il,t}\left(\frac{P_{il,t}}{\tilde{P}_{il,t}}\left(\frac{S^f_{il,t}}{\tilde{S}^f_{fpl,t}}\right)^{\frac{1}{\sigma_p-1}}\tilde{\varphi}_{fpl,t}\right)^{\sigma_p-1}\right)^{\frac{1}{1-\sigma_p}}$$

$$= \tilde{P}_{fpl,t}\left(\sum_{i\in\mathcal{B}_{fpl,t}}\frac{S^f_{il,t}}{\tilde{S}^f_{fpl,t}}\tilde{\varphi}^{\sigma_p-1}_{fpl,t}\right)^{\frac{1}{1-\sigma_p}}$$

To see that the instrument is uncorrelated with the firm-level demand shock, note that:

$$\begin{aligned}\left(\sum_{i\in\mathcal{B}_{fpl,t}}\frac{S^f_{il,t}}{\tilde{S}^f_{fpl,t}}\tilde{\varphi}^{\sigma_p-1}_{fpl,t}\right)^{\frac{1}{1-\sigma_p}} &= \frac{P_{il,t}C_{il,t}}{\left(\prod_{i\in\mathcal{B}_{fpl,t}}\left(P_{il,t}C_{il,t}\right)^{\frac{1}{N_{fpl,t}}}\right.} \\ &= \frac{P_{il,t}C_{il,t}}{\left(\prod_{i\in\mathcal{B}_{fpl,t}}\left(P_{il,t}C_{il,t}\right)^{\frac{1}{N_{fpl,t}}}\right.}\end{aligned}$$

Objective function In the estimation, we rely on the following moment condition $\mathbb{E}_t\left[\varepsilon_{fpl,t}|p^D_{fpl,t},\boldsymbol{\theta},\boldsymbol{\lambda}\right]=0$ and minimize the following GMM-objective function to obtain:

$$\widehat{\eta_p}=\arg\min_{\eta_p}\boldsymbol{M}(\eta_p)'\boldsymbol{W}\boldsymbol{M}(\eta_p)\qquad\forall p\in\mathcal{P}$$

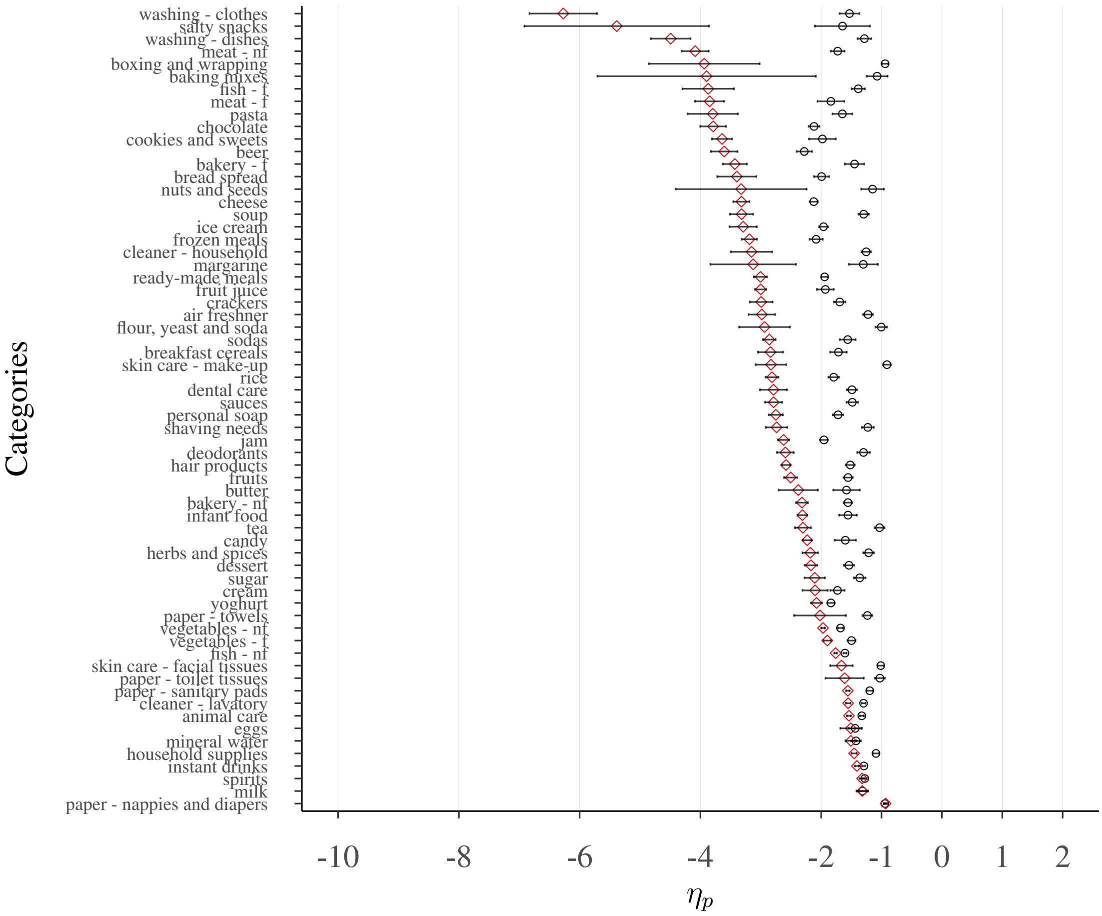
where

$$M_{pfl}(\eta_p)=\mathbb{E}_t\left[p^D_{fpl,t}\varepsilon_{fpl,t}(\eta)\right],\qquad p^D_{fpl,t}\equiv\frac{1}{1-\hat{\sigma}_p}\text{ln}\left(\sum_{i\in\mathcal{B}_{fpl,t}}\frac{S_{il,t}}{\tilde{S}_{fpl,t}}\tilde{\xi}^{\hat{\sigma}_p-1}_{fpl,t}\right)$$

and $\boldsymbol{W}$ is a weighting matrix that weights the variety-region moment conditions using the number of transactions associated with that firm in that region.

D.2.2 Estimation results

Figure D.3: Elasticity of substitution η_p: Weekly frequency $\sum_{t\in y(t)} \mathbb{1}(P_{il,t}C_{il,t} > 0) \geq 0.5$



Notes: This figure shows the OLS and IV-estimates of the firm-level elasticities of substitution η estimated using consumption data at the weekly frequency. The estimations include all firm-region-week observations for which weekly sales are positive in over 50% of weeks in a given year. We include category-firm-region- FEs and category-region-week FEs. Alongside the parameters, we plot 95% confidence intervals based on clustered standard errors at the firm level. For expositional purposes, we omit estimates for which the confidence intervals are outside of the $[-10, 2]$ range.

Table D.3: Weekly Firm-level Elasticities: Dispersion instrument

			Unweighted			Weighted			OLS			IV		
Sample	Specification	nr. Cat	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	p10	p50	p90	p10	p50	p90
Full sample	f-n + p-n-t	68	1.00	0.97	0.01	1.00	0.97	0.01	-1.85	-1.30	-1.01	-4.62	-2.72	-1.42
Full sample	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.08	-1.55	-1.06	-4.49	-2.85	-1.61
Full sample	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.62	-1.83	-1.16	-4.99	-3.11	-1.74
Full sample	f-n-y + f-n-w + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.86	-1.40	-1.01	-4.49	-2.79	-1.52
Full sample	f-n-y + f-n-w + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.06	-1.53	-1.06	-4.49	-2.87	-1.60
Full sample	f-r-y + f-r-w + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.50	-1.78	-1.14	-4.92	-3.10	-1.71
T $\geq$ 25%	f-n + p-n-t	68	1.00	0.97	0.01	1.00	0.97	0.01	-1.86	-1.31	-1.01	-4.62	-2.72	-1.42
T $\geq$ 25%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.12	-1.57	-1.06	-4.49	-2.85	-1.61
T $\geq$ 25%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.67	-1.89	-1.17	-4.92	-3.10	-1.73
T $\geq$ 25%	f-n-y + f-n-w + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.92	-1.44	-1.01	-4.50	-2.80	-1.52
T $\geq$ 25%	f-n-y + f-n-w + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.09	-1.57	-1.06	-4.47	-2.87	-1.60
T $\geq$ 25%	f-r-y + f-r-w + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.55	-1.82	-1.15	-4.86	-3.10	-1.71
T $\geq$ 50%	f-n + p-n-t	68	1.00	0.97	0.01	1.00	0.97	0.01	-1.92	-1.32	-1.02	-4.62	-2.73	-1.43
T $\geq$ 50%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.12	-1.60	-1.06	-4.47	-2.85	-1.61
T $\geq$ 50%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.83	-1.94	-1.16	-4.91	-3.10	-1.73
T $\geq$ 50%	f-n-y + f-n-w + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.96	-1.47	-1.03	-4.49	-2.80	-1.51
T $\geq$ 50%	f-n-y + f-n-w + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.14	-1.61	-1.06	-4.45	-2.87	-1.60
T $\geq$ 50%	f-r-y + f-r-w + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.64	-1.91	-1.15	-4.84	-3.10	-1.71
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.92	-1.39	-1.01	-4.64	-2.73	-1.42
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.13	-1.61	-1.06	-4.49	-2.85	-1.61
T $\geq$ 25% & M $\geq$ 0.1%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.72	-1.93	-1.17	-4.92	-3.10	-1.73
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-w + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.94	-1.45	-1.01	-4.49	-2.80	-1.51
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-w + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.13	-1.61	-1.06	-4.49	-2.87	-1.60
T $\geq$ 25% & M $\geq$ 0.1%	f-r-y + f-r-w + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.61	-1.87	-1.16	-4.87	-3.10	-1.71
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-n-t	68	1.00	0.97	0.01	1.00	0.97	0.01	-1.93	-1.34	-1.02	-4.62	-2.73	-1.43
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.14	-1.62	-1.06	-4.47	-2.85	-1.61
T $\geq$ 50% & M $\geq$ 0.1%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.84	-1.96	-1.16	-4.92	-3.10	-1.73
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-w + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.00	-1.49	-1.03	-4.49	-2.80	-1.51
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-w + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.16	-1.64	-1.06	-4.46	-2.87	-1.60
T $\geq$ 50% & M $\geq$ 0.1%	f-r-y + f-r-w + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.65	-1.93	-1.15	-4.85	-3.10	-1.71

Notes: This table provides an overview of the OLS and IV estimates of the firm-level elasticities of substitution η_p estimated using consumption data at the weekly frequency for different specifications. The sample column indicates which restriction we place on the included sample. The specification columns indicate which sets of fixed effects we include. The nr. Cat shows how many categories the minimization routine for the IV-estimator converged successfully. The unweighted columns plot the fraction of IV estimates which are significantly different from 0, different from -1 and whether any estimates are statistically significantly larger than -1. The weighted column computes weighted shares by weighting each category at its expenditure share. Finally, the OLS and IV columns provide the distribution of OLS and IV estimates across categories respectively. All statistical tests are based on standard errors that are clustered at the variety level.

Table D.4: Monthtly Firm-level Elasticities: Dispersion instrument

			Unweighted			Weighted			OLS			IV		
Sample	Specification	nr. Cat	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	p10	p50	p90	p10	p50	p90
Full sample	f-n + p-n-t	68	1.00	0.93	0.04	1.00	0.92	0.06	-1.67	-1.29	-1.06	-2.36	-1.47	-1.12
Full sample	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.83	-1.35	-1.12	-2.60	-1.53	-1.21
Full sample	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.14	-1.47	-1.20	-3.03	-1.63	-1.30
Full sample	f-n-y + f-n-m + p-n-t	68	1.00	0.94	0.01	1.00	0.93	0.01	-1.70	-1.30	-1.06	-2.42	-1.49	-1.17
Full sample	f-n-y + f-n-m + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-1.79	-1.36	-1.11	-2.48	-1.53	-1.23
Full sample	f-r-y + f-r-m + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.07	-1.47	-1.19	-3.02	-1.61	-1.30
T $\geq$ 25%	f-n + p-n-t	68	1.00	0.94	0.03	0.97	0.94	0.02	-1.75	-1.28	-1.04	-3.41	-1.76	-1.18
T $\geq$ 25%	f-n + p-r-t	69	1.01	0.99	0.03	1.00	0.98	0.02	-1.94	-1.35	-1.08	-3.88	-1.98	-1.28
T $\geq$ 25%	f-r + p-r-t	69	1.01	0.99	0.00	1.00	0.98	0.00	-2.43	-1.51	-1.14	-4.64	-2.18	-1.41
T $\geq$ 25%	f-n-y + f-n-m + p-n-t	68	1.00	0.96	0.03	0.97	0.94	0.02	-1.79	-1.31	-1.03	-3.51	-1.82	-1.26
T $\geq$ 25%	f-n-y + f-n-m + p-r-t	69	1.01	0.99	0.01	1.00	0.98	0.01	-1.90	-1.36	-1.08	-3.77	-1.92	-1.29
T $\geq$ 25%	f-r-y + f-r-m + p-r-t	69	1.01	0.99	0.00	1.00	0.98	0.00	-2.30	-1.50	-1.15	-4.55	-2.17	-1.41
T $\geq$ 50%	f-n + p-n-t	68	1.00	0.93	0.04	1.00	0.92	0.06	-1.69	-1.29	-1.06	-2.74	-1.48	-1.12
T $\geq$ 50%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.84	-1.39	-1.12	-2.85	-1.55	-1.21
T $\geq$ 50%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.14	-1.47	-1.18	-3.20	-1.66	-1.30
T $\geq$ 50%	f-n-y + f-n-m + p-n-t	68	1.00	0.94	0.01	1.00	0.93	0.01	-1.72	-1.32	-1.06	-2.79	-1.49	-1.17
T $\geq$ 50%	f-n-y + f-n-m + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-1.81	-1.38	-1.11	-2.91	-1.54	-1.23
T $\geq$ 50%	f-r-y + f-r-m + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.07	-1.47	-1.18	-3.20	-1.64	-1.30
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-n-t	68	1.00	0.93	0.04	1.00	0.92	0.06	-1.69	-1.29	-1.06	-2.36	-1.47	-1.11
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.84	-1.36	-1.12	-2.60	-1.53	-1.21
T $\geq$ 25% & M $\geq$ 0.1%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.15	-1.48	-1.18	-3.03	-1.62	-1.30
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-m + p-n-t	68	1.00	0.94	0.01	1.00	0.93	0.01	-1.73	-1.33	-1.06	-2.42	-1.49	-1.17
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-m + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-1.81	-1.38	-1.11	-2.48	-1.53	-1.23
T $\geq$ 25% & M $\geq$ 0.1%	f-r-y + f-r-m + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.08	-1.48	-1.18	-3.02	-1.60	-1.30
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-n-t	68	1.00	0.93	0.04	1.00	0.92	0.06	-1.69	-1.29	-1.06	-2.36	-1.47	-1.12
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.84	-1.36	-1.12	-2.60	-1.53	-1.21
T $\geq$ 50% & M $\geq$ 0.1%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.15	-1.48	-1.18	-3.03	-1.62	-1.30
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-m + p-n-t	68	1.00	0.94	0.01	1.00	0.93	0.01	-1.73	-1.33	-1.06	-2.42	-1.49	-1.17
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-m + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-1.82	-1.37	-1.11	-2.48	-1.53	-1.23
T $\geq$ 50% & M $\geq$ 0.1%	f-r-y + f-r-m + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.09	-1.48	-1.18	-3.02	-1.60	-1.30

Notes: This table provides an overview of the OLS and IV-estimates of the firm-level elasticities of substitution η_p estimated using consumption data at the monthly frequency for different specifications. The sample column indicates which restriction we place on the included sample. The specification columns indicate which sets of fixed effects we include. The nr. Cat shows how many categories the minimization routine for the IV-estimator converged successfully. The unweighted columns plot the fraction of IV estimates which are significantly different from 0, different from -1 and whether any estimates are statistically significantly larger than -1. The weighted column computes weighted shares by weighting each category at its expenditure share. Finally, the OLS and IV columns provide the distribution of OLS and IV estimates across categories respectively. All statistical tests are based on standard errors that are clustered at the variety level.

Table D.5: Weekly Firm-level Elasticities: Dispersion instrument - Country comparison

		Belgium			France			The Netherlands			Germany		
Sample	Specification	p10	p50	p90	p10	p50	p90	p10	p50	p90	p10	p50	p90
Full sample	f-n + p-n-t	-4.62	-2.83	-1.47	-5.30	-2.88	-1.54	-4.56	-2.61	-1.32	-4.34	-2.70	-1.38
Full sample	f-n + p-r-t	-4.89	-2.89	-1.54	-5.38	-2.97	-1.60	-4.99	-2.84	-1.47	-4.65	-2.83	-1.63
Full sample	f-r + p-r-t	-2.26	-1.46	-1.01	-2.97	-1.95	-1.30	-3.04	-2.07	-1.12			
Full sample	f-n-y + f-n-w + p-n-t	-4.56	-2.84	-1.48	-5.19	-2.92	-1.57	-5.50	-2.61	-1.35	-4.31	-2.73	-1.43
Full sample	f-n-y + f-n-w + p-r-t	-4.69	-2.82	-1.51	-5.36	-3.00	-1.60	-5.41	-2.73	-1.50	-4.52	-2.86	-1.61
Full sample	f-r-y + f-r-w + p-r-t	-5.33	-3.01	-1.75	-5.84	-3.15	-1.71	-6.79	-3.28	-1.73	-4.94	-2.95	-1.72
T $\geq$ 25%	f-n + p-n-t	-4.62	-2.82	-1.47	-5.30	-2.88	-1.54	-4.56	-2.61	-1.32	-4.34	-2.70	-1.38
T $\geq$ 25%	f-n + p-r-t	-4.88	-2.89	-1.58	-5.38	-2.97	-1.60	-4.98	-2.84	-1.47	-4.64	-2.83	-1.63
T $\geq$ 25%	f-r + p-r-t	-5.58	-3.08	-1.74	-5.71	-3.10	-1.68	-7.01	-3.32	-1.76	-5.10	-2.95	-1.73
T $\geq$ 25%	f-n-y + f-n-w + p-n-t	-4.56	-2.85	-1.48	-5.19	-2.92	-1.57	-5.51	-2.61	-1.35	-4.32	-2.73	-1.43
T $\geq$ 25%	f-n-y + f-n-w + p-r-t	-4.69	-2.83	-1.51	-5.35	-3.00	-1.59	-5.41	-2.72	-1.49	-4.52	-2.87	-1.61
T $\geq$ 25%	f-r-y + f-r-w + p-r-t	-5.33	-3.01	-1.75	-5.65	-3.10	-1.67	-6.79	-3.28	-1.74	-4.94	-2.95	-1.72
T $\geq$ 50%	f-n + p-n-t	-4.66	-2.91	-1.48	-5.31	-2.87	-1.54	-4.57	-2.62	-1.32	-4.33	-2.70	-1.38
T $\geq$ 50%	f-n + p-r-t	-4.88	-2.96	-1.58	-5.40	-2.97	-1.59	-4.98	-2.85	-1.46	-4.62	-2.83	-1.63
T $\geq$ 50%	f-r + p-r-t	-5.63	-3.08	-1.75	-5.72	-3.10	-1.68	-7.01	-3.32	-1.76	-5.08	-2.95	-1.73
T $\geq$ 50%	f-n-y + f-n-w + p-n-t	-4.56	-2.86	-1.49	-5.20	-2.92	-1.57	-5.55	-2.60	-1.35	-4.32	-2.73	-1.43
T $\geq$ 50%	f-n-y + f-n-w + p-r-t	-4.73	-2.91	-1.56	-5.37	-2.99	-1.59	-5.48	-2.72	-1.49	-4.50	-2.88	-1.61
T $\geq$ 50%	f-r-y + f-r-w + p-r-t	-5.37	-3.01	-1.78	-5.66	-3.10	-1.67	-6.78	-3.27	-1.74	-4.93	-2.95	-1.72
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-n-t	-4.62	-2.86	-1.45	-5.49	-2.89	-1.54	-4.38	-2.61	-1.33	-4.45	-2.69	-1.39
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-r-t	-4.88	-2.89	-1.58	-5.39	-2.97	-1.60	-4.99	-2.84	-1.47	-4.65	-2.83	-1.63
T $\geq$ 25% & M $\geq$ 0.1%	f-r + p-r-t	-5.58	-3.08	-1.74	-5.71	-3.10	-1.68	-7.02	-3.32	-1.76	-5.10	-2.95	-1.73
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-w + p-n-t	-4.57	-2.85	-1.48	-5.19	-2.92	-1.57	-5.52	-2.61	-1.35	-4.32	-2.73	-1.43
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-w + p-r-t	-4.72	-2.83	-1.51	-5.36	-3.00	-1.59	-5.41	-2.72	-1.49	-4.51	-2.87	-1.61
T $\geq$ 25% & M $\geq$ 0.1%	f-r-y + f-r-w + p-r-t	-5.33	-3.01	-1.75	-5.66	-3.10	-1.67	-6.79	-3.28	-1.74	-4.94	-2.95	-1.72
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-n-t	-4.66	-2.91	-1.48	-5.32	-2.87	-1.54	-4.57	-2.62	-1.32	-4.33	-2.70	-1.38
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-r-t	-4.89	-2.96	-1.59	-5.41	-2.97	-1.59	-4.99	-2.85	-1.46	-4.62	-2.83	-1.63
T $\geq$ 50% & M $\geq$ 0.1%	f-r + p-r-t	-5.63	-3.08	-1.75	-5.73	-3.10	-1.68	-7.01	-3.32	-1.76	-5.08	-2.95	-1.73
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-w + p-n-t	-4.57	-2.86	-1.49	-5.20	-2.92	-1.57	-5.55	-2.60	-1.35	-4.32	-2.73	-1.43
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-w + p-r-t	-4.73	-2.92	-1.56	-5.38	-2.99	-1.59	-5.48	-2.72	-1.49	-4.49	-2.88	-1.61
T $\geq$ 50% & M $\geq$ 0.1%	f-r-y + f-r-w + p-r-t	-5.37	-3.01	-1.78	-5.67	-3.10	-1.67	-6.78	-3.28	-1.74	-4.93	-2.95	-1.72

Notes: This table provides an overview of the IV estimates of the firm-level elasticities of substitution η_p estimated using consumption data at the weekly frequency for different specifications across the different countries. The sample column indicates which restriction we place on the included sample. The specification columns indicate which sets of fixed effects we include. For each country, we provide the distribution of firm-level elasticities of substitution across the categories.

Table D.6: Weekly Firm-level Elasticities: Dispersion instrument - Belgium

			Unweighted			Weighted			OLS			IV		
Sample	Specification	nr. Cat	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	p10	p50	p90	p10	p50	p90
Full sample	f-n + p-n-t	68	1.00	0.94	0.01	1.00	0.98	0.01	-1.73	-1.24	-0.95	-4.62	-2.83	-1.47
Full sample	f-n + p-r-t	68	0.99	0.94	0.00	0.99	0.98	0.00	-1.81	-1.25	-0.97	-4.89	-2.89	-1.54
Full sample	f-r + p-r-t	68	1.00	0.82	0.01	1.00	0.92	0.01	-2.26	-1.46	-1.01	-2.26	-1.46	-1.01
Full sample	f-n-y + f-n-w + p-n-t	68	0.97	0.93	0.01	0.99	0.97	0.01	-1.72	-1.21	-0.94	-4.56	-2.84	-1.48
Full sample	f-n-y + f-n-w + p-r-t	68	0.97	0.93	0.01	0.99	0.97	0.01	-1.79	-1.25	-0.94	-4.69	-2.82	-1.51
Full sample	f-r-y + f-r-w + p-r-t	68	0.96	0.93	0.00	0.98	0.97	0.00	-2.10	-1.45	-0.99	-5.33	-3.01	-1.75
T $\geq$ 25%	f-n + p-n-t	68	1.00	0.94	0.01	1.00	0.98	0.01	-1.74	-1.25	-0.95	-4.62	-2.82	-1.47
T $\geq$ 25%	f-n + p-r-t	68	0.99	0.94	0.00	0.99	0.98	0.00	-1.88	-1.30	-0.97	-4.88	-2.89	-1.58
T $\geq$ 25%	f-r + p-r-t	68	0.99	0.94	0.00	0.99	0.98	0.00	-2.39	-1.61	-1.06	-5.58	-3.08	-1.74
T $\geq$ 25%	f-n-y + f-n-w + p-n-t	68	0.97	0.93	0.01	0.99	0.97	0.01	-1.79	-1.27	-0.94	-4.56	-2.85	-1.48
T $\geq$ 25%	f-n-y + f-n-w + p-r-t	68	0.97	0.93	0.01	0.99	0.97	0.01	-1.91	-1.32	-0.94	-4.69	-2.83	-1.51
T $\geq$ 25%	f-r-y + f-r-w + p-r-t	68	0.96	0.93	0.00	0.98	0.97	0.00	-2.36	-1.57	-1.01	-5.33	-3.01	-1.75
T $\geq$ 50%	f-n + p-n-t	68	1.00	0.96	0.01	1.00	0.98	0.01	-1.77	-1.29	-0.95	-4.66	-2.91	-1.48
T $\geq$ 50%	f-n + p-r-t	68	0.99	0.96	0.00	0.99	0.98	0.00	-1.93	-1.38	-0.97	-4.88	-2.96	-1.58
T $\geq$ 50%	f-r + p-r-t	68	0.99	0.96	0.00	0.99	0.98	0.00	-2.43	-1.66	-1.09	-5.63	-3.08	-1.75
T $\geq$ 50%	f-n-y + f-n-w + p-n-t	68	0.97	0.94	0.01	0.99	0.98	0.01	-1.83	-1.31	-0.93	-4.56	-2.86	-1.49
T $\geq$ 50%	f-n-y + f-n-w + p-r-t	68	0.97	0.94	0.01	0.99	0.98	0.01	-1.93	-1.39	-0.95	-4.73	-2.91	-1.56
T $\geq$ 50%	f-r-y + f-r-w + p-r-t	68	0.97	0.93	0.00	0.99	0.97	0.00	-2.40	-1.63	-1.07	-5.37	-3.01	-1.78
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-n-t	68	0.99	0.94	0.01	0.99	0.98	0.01	-1.77	-1.27	-0.95	-4.62	-2.86	-1.45
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-r-t	68	0.99	0.94	0.00	0.99	0.98	0.00	-1.90	-1.34	-0.97	-4.88	-2.89	-1.58
T $\geq$ 25% & M $\geq$ 0.1%	f-r + p-r-t	68	0.99	0.94	0.00	0.99	0.98	0.00	-2.40	-1.64	-1.07	-5.58	-3.08	-1.74
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-w + p-n-t	68	0.97	0.93	0.01	0.99	0.97	0.01	-1.84	-1.30	-0.94	-4.57	-2.85	-1.48
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-w + p-r-t	68	0.97	0.93	0.01	0.99	0.97	0.01	-1.93	-1.33	-0.94	-4.72	-2.83	-1.51
T $\geq$ 25% & M $\geq$ 0.1%	f-r-y + f-r-w + p-r-t	68	0.96	0.93	0.00	0.98	0.97	0.00	-2.39	-1.60	-1.01	-5.33	-3.01	-1.75
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-n-t	68	1.00	0.96	0.01	1.00	0.98	0.01	-1.80	-1.30	-0.95	-4.66	-2.91	-1.48
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-r-t	68	0.99	0.96	0.00	0.99	0.98	0.00	-1.93	-1.38	-0.97	-4.89	-2.96	-1.59
T $\geq$ 50% & M $\geq$ 0.1%	f-r + p-r-t	68	0.99	0.96	0.00	0.99	0.98	0.00	-2.43	-1.67	-1.09	-5.63	-3.08	-1.75
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-w + p-n-t	68	0.97	0.94	0.01	0.99	0.98	0.01	-1.86	-1.33	-0.93	-4.57	-2.86	-1.49
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-w + p-r-t	68	0.97	0.94	0.01	0.99	0.98	0.01	-1.95	-1.39	-0.95	-4.73	-2.92	-1.56
T $\geq$ 50% & M $\geq$ 0.1%	f-r-y + f-r-w + p-r-t	68	0.97	0.93	0.00	0.99	0.97	0.00	-2.42	-1.65	-1.07	-5.37	-3.01	-1.78

Notes: This table provides an overview of the OLS and IV estimates of the firm-level elasticities of substitution η_p estimated using consumption data at the weekly frequency for different specifications for Belgium. The sample column indicates which restriction we place on the included sample. The specification columns indicate which sets of fixed effects we include. The nr. Cat shows how many categories the minimization routine for the IV-estimator converged successfully. The unweighted columns plot the fraction of IV estimates which are significantly different from 0, different from -1 and whether any estimates are statistically significantly larger than -1. The weighted column computes weighted shares by weighting each category at its expenditure share. Finally, the OLS and IV columns provide the distribution of OLS and IV estimates across categories respectively. All statistical tests are based on standard errors that are clustered at the variety level.

Table D.7: Weekly Firm-level Elasticities: Dispersion instrument - France

			Unweighted			Weighted			OLS			IV		
Sample	Specification	nr. Cat	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	p10	p50	p90	p10	p50	p90
Full sample	f-n + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.95	-1.42	-1.07	-5.30	-2.88	-1.54
Full sample	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.21	-1.55	-1.15	-5.38	-2.97	-1.60
Full sample	f-r + p-r-t	68	1.00	0.97	0.01	1.00	0.98	0.01	-2.97	-1.95	-1.30	-2.97	-1.95	-1.30
Full sample	f-n-y + f-n-w + p-n-t	68	0.99	0.97	0.01	0.99	0.99	0.01	-1.98	-1.41	-1.08	-5.19	-2.92	-1.57
Full sample	f-n-y + f-n-w + p-r-t	68	0.99	0.97	0.01	0.99	0.99	0.01	-2.24	-1.54	-1.14	-5.36	-3.00	-1.60
Full sample	f-r-y + f-r-w + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.81	-1.90	-1.29	-5.84	-3.15	-1.71
T ≥ 25%	f-n + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.97	-1.45	-1.08	-5.30	-2.88	-1.54
T ≥ 25%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.24	-1.59	-1.18	-5.38	-2.97	-1.60
T ≥ 25%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.87	-1.88	-1.27	-5.71	-3.10	-1.68
T ≥ 25%	f-n-y + f-n-w + p-n-t	68	0.99	0.96	0.01	0.99	0.98	0.01	-2.05	-1.45	-1.11	-5.19	-2.92	-1.57
T ≥ 25%	f-n-y + f-n-w + p-r-t	68	0.99	0.96	0.01	0.99	0.98	0.01	-2.30	-1.58	-1.17	-5.35	-3.00	-1.59
T ≥ 25%	f-r-y + f-r-w + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.76	-1.87	-1.26	-5.65	-3.10	-1.67
T ≥ 50%	f-n + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.00	-1.50	-1.10	-5.31	-2.87	-1.54
T ≥ 50%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.28	-1.63	-1.19	-5.40	-2.97	-1.59
T ≥ 50%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.94	-1.94	-1.28	-5.72	-3.10	-1.68
T ≥ 50%	f-n-y + f-n-w + p-n-t	68	0.97	0.96	0.01	0.98	0.98	0.01	-2.09	-1.52	-1.12	-5.20	-2.92	-1.57
T ≥ 50%	f-n-y + f-n-w + p-r-t	68	0.97	0.96	0.01	0.98	0.98	0.01	-2.31	-1.62	-1.20	-5.37	-2.99	-1.59
T ≥ 50%	f-r-y + f-r-w + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.93	-1.92	-1.28	-5.66	-3.10	-1.67
T ≥ 25% & M ≥ 0.1%	f-n + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-1.98	-1.44	-1.10	-5.49	-2.89	-1.54
T ≥ 25% & M ≥ 0.1%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.25	-1.59	-1.18	-5.39	-2.97	-1.60
T ≥ 25% & M ≥ 0.1%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.88	-1.89	-1.27	-5.71	-3.10	-1.68
T ≥ 25% & M ≥ 0.1%	f-n-y + f-n-w + p-n-t	68	0.99	0.96	0.01	0.99	0.98	0.01	-2.06	-1.46	-1.11	-5.19	-2.92	-1.57
T ≥ 25% & M ≥ 0.1%	f-n-y + f-n-w + p-r-t	68	0.99	0.96	0.01	0.99	0.98	0.01	-2.31	-1.60	-1.17	-5.36	-3.00	-1.59
T ≥ 25% & M ≥ 0.1%	f-r-y + f-r-w + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.79	-1.87	-1.26	-5.66	-3.10	-1.67
T ≥ 50% & M ≥ 0.1%	f-n + p-n-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.00	-1.50	-1.10	-5.32	-2.87	-1.54
T ≥ 50% & M ≥ 0.1%	f-n + p-r-t	68	1.00	0.99	0.01	1.00	0.99	0.01	-2.29	-1.63	-1.19	-5.41	-2.97	-1.59
T ≥ 50% & M ≥ 0.1%	f-r + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.95	-1.94	-1.28	-5.73	-3.10	-1.68
T ≥ 50% & M ≥ 0.1%	f-n-y + f-n-w + p-n-t	68	0.97	0.96	0.01	0.98	0.98	0.01	-2.08	-1.52	-1.12	-5.20	-2.92	-1.57
T ≥ 50% & M ≥ 0.1%	f-n-y + f-n-w + p-r-t	68	0.97	0.96	0.01	0.98	0.98	0.01	-2.31	-1.62	-1.20	-5.38	-2.99	-1.59
T ≥ 50% & M ≥ 0.1%	f-r-y + f-r-w + p-r-t	68	1.00	0.99	0.00	1.00	0.99	0.00	-2.94	-1.92	-1.28	-5.67	-3.10	-1.67

Notes: This table provides an overview of the OLS and IV estimates of the firm-level elasticities of substitution η_p estimated using consumption data at the weekly frequency for different specifications for France. The sample column indicates which restriction we place on the included sample. The specification columns indicate which sets of fixed effects we include. The nr. Cat shows how many categories the minimization routine for the IV-estimator converged successfully. The unweighted columns plot the fraction of IV estimates which are significantly different from 0, different from -1 and whether any estimates are statistically significantly larger than -1. The weighted column computes weighted shares by weighting each category at its expenditure share. Finally, the OLS and IV columns provide the distribution of OLS and IV estimates across categories respectively. All statistical tests are based on standard errors that are clustered at the variety level.

Table D.8: Weekly Firm-level Elasticities: Dispersion instrument - The Netherlands

			Unweighted			Weighted			OLS			IV		
Sample	Specification	nr. Cat	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	p10	p50	p90	p10	p50	p90
Full sample	f-n + p-n-t	68	0.99	0.91	0.03	1.00	0.94	0.01	-1.89	-1.32	-0.94	-4.56	-2.61	-1.32
Full sample	f-n + p-r-t	68	1.00	0.97	0.03	1.00	0.99	0.01	-2.11	-1.52	-1.03	-4.99	-2.84	-1.47
Full sample	f-r + p-r-t	68	1.00	0.90	0.03	1.00	0.95	0.01	-3.04	-2.07	-1.12	-3.04	-2.07	-1.12
Full sample	f-n-y + f-n-w + p-n-t	68	0.96	0.90	0.01	0.95	0.92	0.01	-1.87	-1.40	-0.98	-5.50	-2.61	-1.35
Full sample	f-n-y + f-n-w + p-r-t	68	0.99	0.96	0.00	0.98	0.97	0.00	-2.02	-1.54	-1.04	-5.41	-2.73	-1.50
Full sample	f-r-y + f-r-w + p-r-t	68	0.99	0.96	0.00	0.98	0.97	0.00	-2.76	-2.01	-1.09	-6.79	-3.28	-1.73
T $\geq$ 25%	f-n + p-n-t	68	0.99	0.91	0.03	1.00	0.94	0.01	-1.93	-1.36	-0.94	-4.56	-2.61	-1.32
T $\geq$ 25%	f-n + p-r-t	68	1.00	0.97	0.03	1.00	0.99	0.01	-2.17	-1.55	-1.03	-4.98	-2.84	-1.47
T $\geq$ 25%	f-r + p-r-t	68	1.00	0.97	0.00	1.00	0.99	0.00	-3.13	-2.11	-1.13	-7.01	-3.32	-1.76
T $\geq$ 25%	f-n-y + f-n-w + p-n-t	68	0.96	0.90	0.01	0.95	0.92	0.01	-1.92	-1.44	-0.99	-5.51	-2.61	-1.35
T $\geq$ 25%	f-n-y + f-n-w + p-r-t	68	0.99	0.94	0.00	0.98	0.96	0.00	-2.08	-1.56	-1.05	-5.41	-2.72	-1.49
T $\geq$ 25%	f-r-y + f-r-w + p-r-t	68	0.99	0.96	0.00	0.98	0.97	0.00	-2.81	-2.06	-1.11	-6.79	-3.28	-1.74
T $\geq$ 50%	f-n + p-n-t	68	0.99	0.91	0.03	1.00	0.94	0.01	-1.96	-1.39	-0.95	-4.57	-2.62	-1.32
T $\geq$ 50%	f-n + p-r-t	68	1.00	0.97	0.03	1.00	0.99	0.01	-2.26	-1.56	-1.04	-4.98	-2.85	-1.46
T $\geq$ 50%	f-r + p-r-t	68	1.00	0.97	0.00	1.00	0.99	0.00	-3.16	-2.17	-1.16	-7.01	-3.32	-1.76
T $\geq$ 50%	f-n-y + f-n-w + p-n-t	68	0.96	0.90	0.00	0.95	0.92	0.00	-1.96	-1.46	-0.99	-5.55	-2.60	-1.35
T $\geq$ 50%	f-n-y + f-n-w + p-r-t	68	0.97	0.94	0.00	0.96	0.96	0.00	-2.11	-1.58	-1.06	-5.48	-2.72	-1.49
T $\geq$ 50%	f-r-y + f-r-w + p-r-t	68	0.99	0.96	0.00	0.98	0.97	0.00	-2.95	-2.10	-1.17	-6.78	-3.27	-1.74
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-n-t	68	0.99	0.90	0.01	1.00	0.93	0.01	-2.01	-1.41	-0.96	-4.38	-2.61	-1.33
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-r-t	68	1.00	0.97	0.03	1.00	0.99	0.01	-2.32	-1.55	-1.03	-4.99	-2.84	-1.47
T $\geq$ 25% & M $\geq$ 0.1%	f-r + p-r-t	68	1.00	0.97	0.00	1.00	0.99	0.00	-3.18	-2.15	-1.13	-7.02	-3.32	-1.76
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-w + p-n-t	68	0.96	0.90	0.01	0.95	0.92	0.01	-1.99	-1.47	-0.99	-5.52	-2.61	-1.35
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-w + p-r-t	68	0.99	0.94	0.00	0.98	0.96	0.00	-2.29	-1.57	-1.05	-5.41	-2.72	-1.49
T $\geq$ 25% & M $\geq$ 0.1%	f-r-y + f-r-w + p-r-t	68	0.99	0.96	0.00	0.98	0.97	0.00	-2.98	-2.11	-1.11	-6.79	-3.28	-1.74
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-n-t	68	0.99	0.91	0.03	1.00	0.94	0.01	-1.97	-1.39	-0.95	-4.57	-2.62	-1.32
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-r-t	68	1.00	0.97	0.03	1.00	0.99	0.01	-2.35	-1.58	-1.04	-4.99	-2.85	-1.46
T $\geq$ 50% & M $\geq$ 0.1%	f-r + p-r-t	68	1.00	0.97	0.00	1.00	0.99	0.00	-3.27	-2.20	-1.16	-7.01	-3.32	-1.76
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-w + p-n-t	68	0.96	0.90	0.00	0.95	0.92	0.00	-2.00	-1.48	-0.99	-5.55	-2.60	-1.35
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-w + p-r-t	68	0.97	0.94	0.00	0.96	0.96	0.00	-2.31	-1.59	-1.06	-5.48	-2.72	-1.49
T $\geq$ 50% & M $\geq$ 0.1%	f-r-y + f-r-w + p-r-t	68	0.99	0.96	0.00	0.98	0.97	0.00	-3.02	-2.13	-1.17	-6.78	-3.28	-1.74

Notes: This table provides an overview of the OLS and IV estimates of the firm-level elasticities of substitution η_p estimated using consumption data at the weekly frequency for different specifications for The Netherlands. The sample column indicates which restriction we place on the included sample. The specification columns indicate which sets of fixed effects we include. The nr. Cat shows how many categories the minimization routine for the IV-estimator converged successfully. The unweighted columns plot the fraction of IV estimates which are significantly different from 0, different from -1 and whether any estimates are statistically significantly larger than -1. The weighted column computes weighted shares by weighting each category at its expenditure share. Finally, the OLS and IV columns provide the distribution of OLS and IV estimates across categories respectively. All statistical tests are based on standard errors that are clustered at the variety level.

Table D.9: Weekly Firm-level Elasticities: Dispersion instrument - Germany

			Unweighted			Weighted			OLS			IV		
Sample	Specification	nr. Cat	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	$\hat{\beta}_{2SLS} \neq 0$	$\hat{\beta}_{2SLS} \neq -1$	$\hat{\beta}_{2SLS} > -1$	p10	p50	p90	p10	p50	p90
Full sample	f-n + p-n-t	68	0.97	0.94	0.01	0.99	0.95	0.01	-1.95	-1.35	-0.99	-4.34	-2.70	-1.38
Full sample	f-n + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.16	-1.55	-1.03	-4.65	-2.83	-1.63
Full sample	f-r + p-r-t	0	0.00	0.00	0.00	0.00	0.00	0.00	-2.48	-1.76	-1.04			
Full sample	f-n-y + f-n-w + p-n-t	68	0.96	0.93	0.01	0.96	0.95	0.01	-1.92	-1.38	-0.98	-4.31	-2.73	-1.43
Full sample	f-n-y + f-n-w + p-r-t	68	0.96	0.94	0.01	0.96	0.96	0.01	-2.14	-1.56	-1.02	-4.52	-2.86	-1.61
Full sample	f-r-y + f-r-w + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.40	-1.74	-1.04	-4.94	-2.95	-1.72
T $\geq$ 25%	f-n + p-n-t	68	0.97	0.94	0.01	0.99	0.95	0.01	-1.97	-1.35	-0.99	-4.34	-2.70	-1.38
T $\geq$ 25%	f-n + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.24	-1.59	-1.03	-4.64	-2.83	-1.63
T $\geq$ 25%	f-r + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.60	-1.80	-1.05	-5.10	-2.95	-1.73
T $\geq$ 25%	f-n-y + f-n-w + p-n-t	68	0.96	0.93	0.01	0.96	0.95	0.01	-1.98	-1.43	-0.98	-4.32	-2.73	-1.43
T $\geq$ 25%	f-n-y + f-n-w + p-r-t	68	0.96	0.94	0.01	0.96	0.96	0.01	-2.22	-1.60	-1.02	-4.52	-2.87	-1.61
T $\geq$ 25%	f-r-y + f-r-w + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.50	-1.79	-1.04	-4.94	-2.95	-1.72
T $\geq$ 50%	f-n + p-n-t	68	0.97	0.94	0.01	0.99	0.95	0.01	-2.00	-1.37	-0.98	-4.33	-2.70	-1.38
T $\geq$ 50%	f-n + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.32	-1.60	-1.03	-4.62	-2.83	-1.63
T $\geq$ 50%	f-r + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.66	-1.83	-1.06	-5.08	-2.95	-1.73
T $\geq$ 50%	f-n-y + f-n-w + p-n-t	68	0.96	0.93	0.01	0.96	0.95	0.01	-2.03	-1.45	-0.98	-4.32	-2.73	-1.43
T $\geq$ 50%	f-n-y + f-n-w + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.25	-1.61	-1.01	-4.50	-2.88	-1.61
T $\geq$ 50%	f-r-y + f-r-w + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.56	-1.81	-1.04	-4.93	-2.95	-1.72
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-n-t	68	0.96	0.93	0.01	0.98	0.95	0.01	-1.99	-1.39	-0.99	-4.45	-2.69	-1.39
T $\geq$ 25% & M $\geq$ 0.1%	f-n + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.24	-1.60	-1.03	-4.65	-2.83	-1.63
T $\geq$ 25% & M $\geq$ 0.1%	f-r + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.60	-1.82	-1.05	-5.10	-2.95	-1.73
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-w + p-n-t	68	0.96	0.93	0.01	0.96	0.95	0.01	-2.01	-1.48	-0.98	-4.32	-2.73	-1.43
T $\geq$ 25% & M $\geq$ 0.1%	f-n-y + f-n-w + p-r-t	68	0.96	0.94	0.01	0.96	0.96	0.01	-2.23	-1.61	-1.02	-4.51	-2.87	-1.61
T $\geq$ 25% & M $\geq$ 0.1%	f-r-y + f-r-w + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.54	-1.80	-1.04	-4.94	-2.95	-1.72
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-n-t	68	0.97	0.94	0.01	0.99	0.95	0.01	-2.00	-1.39	-0.98	-4.33	-2.70	-1.38
T $\geq$ 50% & M $\geq$ 0.1%	f-n + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.34	-1.61	-1.03	-4.62	-2.83	-1.63
T $\geq$ 50% & M $\geq$ 0.1%	f-r + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.68	-1.84	-1.06	-5.08	-2.95	-1.73
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-w + p-n-t	68	0.96	0.93	0.01	0.96	0.95	0.01	-2.03	-1.48	-0.98	-4.32	-2.73	-1.43
T $\geq$ 50% & M $\geq$ 0.1%	f-n-y + f-n-w + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.26	-1.63	-1.01	-4.49	-2.88	-1.61
T $\geq$ 50% & M $\geq$ 0.1%	f-r-y + f-r-w + p-r-t	68	0.96	0.94	0.00	0.96	0.96	0.00	-2.58	-1.82	-1.04	-4.93	-2.95	-1.72

Notes: This table provides an overview of the OLS and IV-estimates of the firm-level elasticities of substitution η_p estimated using consumption data at the weekly frequency for different specifications for Germany. The sample column indicates which restriction we place on the included sample. The specification columns indicate which sets of fixed effects we include. The nr. Cat shows how many categories the minimization routine for the IV-estimator converged successfully. The unweighted columns plot the fraction of IV estimates which are significantly different from 0, different from -1 and whether any estimates are statistically significantly larger than -1. The weighted column computes weighted shares by weighting each category at its expenditure share. Finally, the OLS and IV columns provide the distribution of OLS and IV estimates across categories respectively. All statistical tests are based on standard errors that are clustered at the variety level.

D.3 Structural components

E Geographic Market Segmentation

E.1 Cross-border shopping

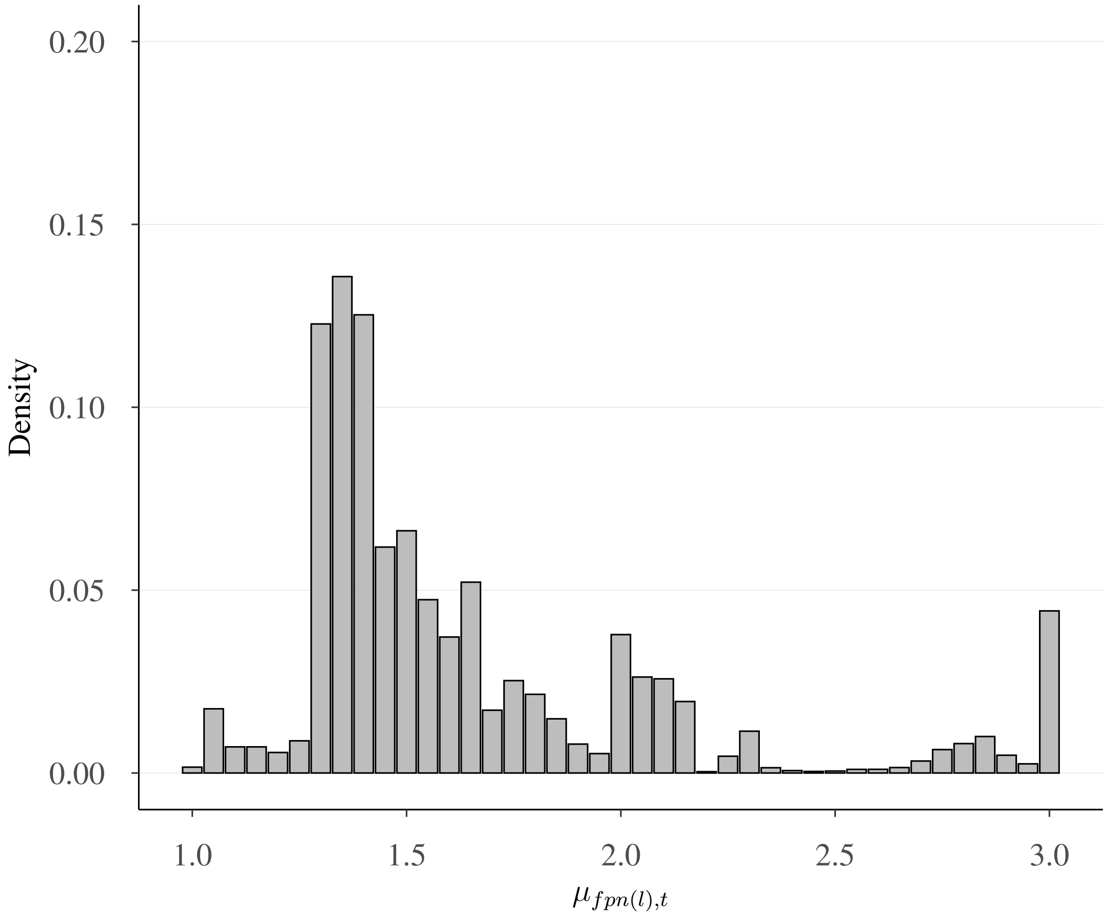
Table E.1: Cross-border shopping - Overall

	Total		Share	
Store region	Transaction	Sales	Transaction	Sales
Belgium	55,221,132	174,211,718	0.979	0.978
France	216,535	797,661	0.004	0.004
The Netherlands	522,119	1,408,998	0.009	0.008
Other foreign	462,753	1,490,103	0.008	0.008
Unknown	11,331	138,077	0.000	0.001

Notes: This table provides the total number of transactions, the total expenditure, the share in the total number of transactions and the share in total expenditure for stores located in Belgium, France, the Netherlands, in another country and for stores which we cannot locate. To obtain these numbers we include all purchases made by Belgian households for the full sample period. Expenditure is expressed in EUR.

E.2 Estimation results

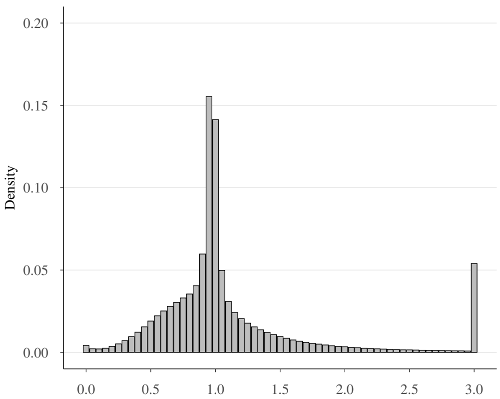
Figure D.4: Firm-level markup distribution



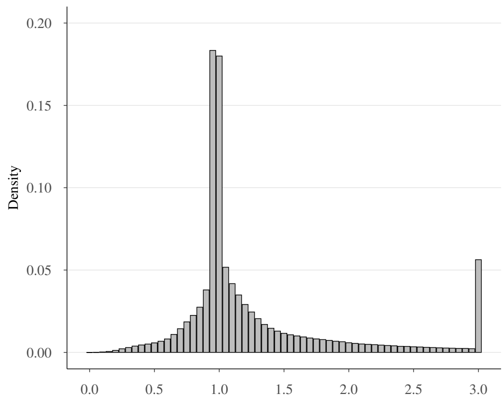
Notes: This figure plots the distribution of firm-level markups. To account for the sampling variation in the elasticities of substitution, we bootstrap the markup distribution. In practice, we draw from the limiting distribution of the firm-level elasticities of substitution and for each bootstrap sample, we compute firm-level markups at the category-firm-country-year level. Hereafter, we bin the absolute markup estimates into 40 separate bins and compute for each bin the number of observations that fall into each bin. Finally, we winsorize the markup distribution at a markup of 3.

Figure D.5: Relative expenditure shares

(a) $\lambda^{B,ll'}_{pl',t} \Big/ \lambda^{B,ll'}_{pl,t}$



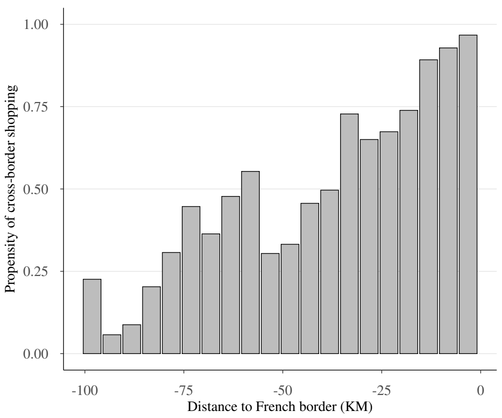
(b) $\lambda^{F,ll'}_{pl',t} \Big/ \lambda^{F,ll'}_{pl,t}$



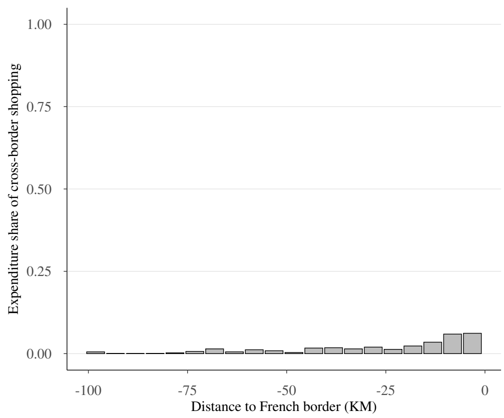
Notes: This figure plots the distribution for the relative expenditure share on common varieties and common firms in panel (a) and panel (b) respectively. The unit of observation is at the category-region l-region l'-year level. Within each category, we compute for each NUTS2-region combination the ratio of expenditure on either common varieties or common firms relative total expenditure. Hereafter, we bin the data into 0.05 bins and winsorize the data at a relative share of 3.

Figure E.1: Cross-border shopping - Distance to the border

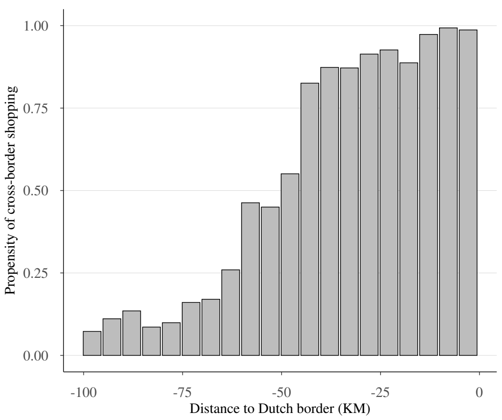
(a) France - Propensity



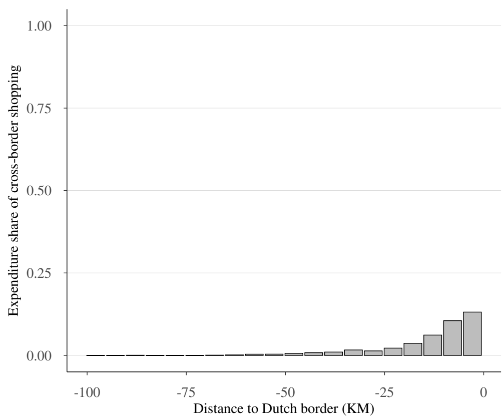
(b) France - Expenditure



(c) The Netherlands - Propensity



(d) The Netherlands - Expenditure



Notes: These figures plot the prevalence of cross-border shopping for Belgian households. Panel (a) and panel (c) plot the share of households that engages at least once in cross-border shopping over the full sample period in either France or the Netherlands as a function of their distance to the respective border. Panel (b) and panel (d) plot the share in total expenditure that accounts for cross-border shopping in either France or the Netherlands as a function of their distance to the respective border. To obtain these numbers we include all households for which we observe their ZIPcode. If so, we compute the smallest great arc distance from the respective ZIPcode to the national border. Given these distances, we create 5km-wide bins to which we allocate households based on their distance to the border. To compute the propensity to engage in cross-border shopping we compute in each distance bin the sum of population weights of the group of people that engages in cross-border shopping. To compute the expenditure share we compute a weighted average of individual household expenditure shares on cross-border transactions by their population weight in each distance bin.

Table E.2: Geographic market segmentation: Robustness - Cutoff: 10% and Nr. controls: 2

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.3956***	.3191***	.0969***	.3016***
	$[.3725, .4344]$	$[.3025, .3451]$	$[.0959, .0978]$	$[.281, .3295]$
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2499	.2293	.0125	.0407
Nr. treated	153	153	153	153
Nr. matched units	2	2	2	2
Nr. unique controls	106	106	106	106
Nr. obs	18,607	18,607	18,607	18,607
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0164***	.0168***	.0061***	.0173***
	$[.0126, .0196]$	$[.014, .0197]$	$[.0058, .0064]$	$[.0156, .0192]$
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4061	.3484	.0242	.0906
Nr. treated	620	620	620	620
Nr. matched units	2	2	2	2
Nr. unique controls	109	109	109	109
Nr. obs	72,852	72,852	72,852	72,852

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $10\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from two matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, column (3) for price differences $\left(L^{kl}_{p,t}\right)$ and column (4) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.3: Geographic market segmentation: Robustness - Cutoff: 10% and Nr. controls: 3

Y	$P_{p,t}^{kl}$	$T_{p,t}^{kl}$	$L_{p,t}^{kl}$	$\Lambda_{p,t}^{kl}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.395***	.3186***	.0968***	.3006***
	[.3696, .4338]	[.3016, .3439]	[.0958, .0976]	[.2803, .329]
$\mathbb{E}\left[\hat{Y}_{p,t}^{kl}(0)\right]$	.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]
$\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}(0)\right]$	.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: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $10\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from three matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P_{p,t}^{kl}\right)$, column (2) for taste differences $\left(T_{p,t}^{kl}\right)$, column (3) for price differences $\left(L_{p,t}^{kl}\right)$ and column (4) for product availability differences $\left(\Lambda_{p,t}^{kl}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.4: Geographic market segmentation: Robustness - Cutoff: 20% and Nr. controls: 1

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.3988***	.316***	.0912***	.3245***
	[.3713, .4409]	[.2969, .3382]	[.0905, .0921]	[.3036, .3578]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2618	.2388	.0125	.0417
Nr. treated	344	344	344	344
Nr. matched units	1	1	1	1
Nr. unique controls	146	146	146	146
Nr. obs	23,392	23,392	23,392	23,392
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0207***	.0214***	.0067***	.0193***
	[.0168, .0245]	[.0177, .0251]	[.0064, .0069]	[.0177, .0215]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4115	.3527	.0246	.0911
Nr. treated	1,342	1,342	1,342	1,342
Nr. matched units	1	1	1	1
Nr. unique controls	135	135	135	135
Nr. obs	89,537	89,537	89,537	89,537

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $20\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from one matched domestic region pair. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, column (3) for price differences $\left(L^{kl}_{p,t}\right)$ and column (4) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.5: Geographic market segmentation: Robustness - Cutoff: 20% and Nr. controls: 2

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.4025***	.3185***	.0912***	.3262***
	[.3762, .4454]	[.2996, .3418]	[.0907, .0917]	[.3047, .3591]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2599	.2378	.0127	.0412
Nr. treated	359	359	359	359
Nr. matched units	2	2	2	2
Nr. unique controls	188	188	188	188
Nr. obs	44,388	44,388	44,388	44,388
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0284***	.0265***	.0065***	.021***
	[.0256, .0316]	[.0237, .0296]	[.0062, .0067]	[.0192, .0234]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4029	.3466	.0249	.0897
Nr. treated	1,361	1,361	1,361	1,361
Nr. matched units	2	2	2	2
Nr. unique controls	139	139	139	139
Nr. obs	165,589	165,589	165,589	165,589

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $20\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from two matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, column (3) for price differences $\left(L^{kl}_{p,t}\right)$ and column (4) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.6: Geographic market segmentation: Robustness - Cutoff: 20% and Nr. controls: 3

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.4067***	.3213***	.0907***	.3255***
	[.381, .4509]	[.3026, .3455]	[.0902, .0912]	[.3042, .3585]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2558	.2341	.0128	.041
Nr. treated	359	359	359	359
Nr. matched units	3	3	3	3
Nr. unique controls	211	211	211	211
Nr. obs	63,493	63,493	63,493	63,493
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0303***	.0278***	.0066***	.0219***
	[.0279, .0334]	[.0254, .031]	[.0063, .0068]	[.02, .0244]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4022	.3463	.0248	.0894
Nr. treated	1,361	1,361	1,361	1,361
Nr. matched units	3	3	3	3
Nr. unique controls	140	140	140	140
Nr. obs	228,673	228,673	228,673	228,673

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $10\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from three matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, column (3) for price differences $\left(L^{kl}_{p,t}\right)$ and column (4) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.7: Geographic market segmentation: Robustness - Cutoff: 15% and Nr. controls: 1

Y	$P_{p,t}^{kl}$	$T_{p,t}^{kl}$	$L_{p,t}^{kl}$	$\Lambda_{p,t}^{kl}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.3828***	.3063***	.0933***	.3093***
	[.3576, .4202]	[.2877, .3273]	[.0924, .0942]	[.289, .3408]
$\mathbb{E}\left[\hat{Y}_{p,t}^{kl}(0)\right]$	.267	.2432	.0128	.0433
Nr. treated	248	248	248	248
Nr. matched units	1	1	1	1
Nr. unique controls	116	116	116	116
Nr. obs	16,864	16,864	16,864	16,864
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0166***	.0181***	.0063***	.0171***
	[.0127, .0206]	[.015, .0214]	[.006, .0066]	[.0153, .019]
$\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}(0)\right]$	.4116	.3528	.0245	.0913
Nr. treated	977	977	977	977
Nr. matched units	1	1	1	1
Nr. unique controls	124	124	124	124
Nr. obs	65,186	65,186	65,186	65,186

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $15\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from one matched domestic region pair. Column (1) shows the results for cost-of-living differences $\left(P_{p,t}^{kl}\right)$, column (2) for taste differences $\left(T_{p,t}^{kl}\right)$, column (3) for price differences $\left(L_{p,t}^{kl}\right)$ and column (4) for product availability differences $\left(\Lambda_{p,t}^{kl}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.8: Geographic market segmentation: Robustness - Cutoff: 15% and Nr. controls: 2

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.3939***	.3154***	.0932***	.3131***
	[.3694, .4347]	[.2969, .3379]	[.0926, .0938]	[.2925, .3443]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2617	.2394	.0129	.0421
Nr. treated	255	255	255	255
Nr. matched units	2	2	2	2
Nr. unique controls	145	145	145	145
Nr. obs	31,334	31,334	31,334	31,334
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0241***	.0228***	.006***	.0189***
	[.0215, .027]	[.0198, .026]	[.0058, .0063]	[.0172, .0211]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4023	.3462	.0248	.0896
Nr. treated	990	990	990	990
Nr. matched units	2	2	2	2
Nr. unique controls	130	130	130	130
Nr. obs	119,286	119,286	119,286	119,286

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $15\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from two matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, column (3) for price differences $\left(L^{kl}_{p,t}\right)$ and column (4) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.9: Geographic market segmentation: Robustness - Cutoff: 15% and Nr. controls: 3

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.3994***	.3198***	.0931***	.3121***
	[.3743, .4415]	[.301, .3451]	[.0924, .0935]	[.2918, .3428]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2545	.2333	.0129	.0412
Nr. treated	255	255	255	255
Nr. matched units	3	3	3	3
Nr. unique controls	161	161	161	161
Nr. obs	44,319	44,319	44,319	44,319
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0248***	.0232***	.0062***	.0199***
	[.0221, .0273]	[.021, .0261]	[.0059, .0064]	[.0182, .0223]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4035	.3474	.0248	.0895
Nr. treated	990	990	990	990
Nr. matched units	3	3	3	3
Nr. unique controls	133	133	133	133
Nr. obs	163,647	163,647	163,647	163,647

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $15\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from three matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, column (3) for price differences $\left(L^{kl}_{p,t}\right)$ and column (4) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.10: Geographic market segmentation: Robustness - Cutoff: 5% and Nr. controls: 1

Y	$P_{p,t}^{kl}$	$T_{p,t}^{kl}$	$L_{p,t}^{kl}$	$\Lambda_{p,t}^{kl}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.369***	.3009***	.1009***	.2685***
	[.3443, .3979]	[.2799, .3238]	[.0991, .1028]	[.2502, .2924]
$\mathbb{E}\left[\hat{Y}_{p,t}^{kl}(0)\right]$	.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]
$\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}(0)\right]$	.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: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $5\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from one matched domestic region pair. Column (1) shows the results for cost-of-living differences $\left(P_{p,t}^{kl}\right)$, column (2) for taste differences $\left(T_{p,t}^{kl}\right)$, column (3) for price differences $\left(L_{p,t}^{kl}\right)$ and column (4) for product availability differences $\left(\Lambda_{p,t}^{kl}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.11: Geographic market segmentation: Robustness - Cutoff: 5% and Nr. controls: 2

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.3793***	.3088***	.1023***	.2712***
	[.3512, .4158]	[.2871, .3379]	[.1009, .1035]	[.2527, .2945]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2409	.2221	.0125	.0411
Nr. treated	75	75	75	75
Nr. matched units	2	2	2	2
Nr. unique controls	50	50	50	50
Nr. obs	8,387	8,387	8,387	8,387
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0064**	.0063***	.0058***	.0157***
	[.0006, .012]	[.0015, .0121]	[.0054, .0061]	[.014, .0176]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.402	.3461	.0238	.0888
Nr. treated	271	271	271	271
Nr. matched units	2	2	2	2
Nr. unique controls	72	72	72	72
Nr. obs	29,809	29,809	29,809	29,809

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $5\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from two matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, column (3) for price differences $\left(L^{kl}_{p,t}\right)$ and column (4) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.12: Geographic market segmentation: Robustness - Cutoff: 5% and Nr. controls: 3

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	.3753***	.3045***	.1036***	.2681***
	[.3491, .4114]	[.283, .3327]	[.1024, .1045]	[.2494, .2909]
$\mathbb{E}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2381	.2202	.0124	.0399
Nr. treated	75	75	75	75
Nr. matched units	3	3	3	3
Nr. unique controls	53	53	53	53
Nr. obs	11,675	11,675	11,675	11,675
USA				
$\hat{\gamma}_{Y,\varepsilon}$	.0107***	.0094***	.0057***	.0167***
	[.0074, .015]	[.0055, .0135]	[.0054, .006]	[.0151, .0187]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4026	.3466	.024	.0895
Nr. treated	272	272	272	272
Nr. matched units	3	3	3	3
Nr. unique controls	79	79	79	79
Nr. obs	39,572	39,572	39,572	39,572

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $5\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from three matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, column (3) for price differences $\left(L^{kl}_{p,t}\right)$ and column (4) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.13: Geographic market segmentation: Robustness - Cutoff: 10% and Nr. controls: 1

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: This table presents the results of applying the matching estimator to cost-of-living, taste, marginal cost, markups and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $10\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from one matched domestic region pair. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, columns (3) and (4) for marginal cost $\left(MC^{kl}_{p,t}\right)$ and markup differences $\left(\mathcal{M}^{kl}_{p,t}\right)$ and column (5) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.14: Geographic market segmentation: Robustness - Cutoff: 10% and Nr. controls: 2

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					
$\hat{\gamma}_{Y,\varepsilon}$	.3956***	.3191***	.0918***	.0114***	.3016***
	[.3725, .4344]	[.3025, .3451]	[.0907, .0929]	[.0108, .012]	[.281, .3295]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2499	.2293	.0211	.0143	.0407
Nr. treated	153	153	153	153	153
Nr. matched units	2	2	2	2	2
Nr. unique controls	106	106	106	106	106
Nr. obs	18,607	18,607	18,607	18,607	18,607
USA					
$\hat{\gamma}_{Y,\varepsilon}$	.0164***	.0168***	.0059***	.0025***	.0173***
	[.0126, .0196]	[.014, .0197]	[.0054, .0063]	[.002, .0029]	[.0156, .0192]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4061	.3484	.038	.0243	.0906
Nr. treated	0	0	0	0	0
Nr. matched units	2	2	2	2	2
Nr. unique controls	0	0	0	0	0
Nr. obs	72,852	72,852	72,852	72,852	72,852

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, marginal cost, markups and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $10\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from two matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, columns (3) and (4) for marginal cost $\left(MC^{kl}_{p,t}\right)$ and markup differences $\left(\mathcal{M}^{kl}_{p,t}\right)$ and column (5) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.15: Geographic market segmentation: Robustness - Cutoff: 10% and Nr. controls: 3

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					
$\hat{\gamma}_{Y,\varepsilon}$	.395***	.3186***	.092***	.0115***	.3006***
	[.3696, .4338]	[.3016, .3439]	[.0911, .093]	[.011, .0122]	[.2803, .329]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.2466	.2265	.0211	.0143	.0402
Nr. treated	154	154	154	154	154
Nr. matched units	3	3	3	3	3
Nr. unique controls	116	116	116	116	116
Nr. obs	26,192	26,192	26,192	26,192	26,192
USA					
$\hat{\gamma}_{Y,\varepsilon}$	.0177***	.0173***	.0061***	.0028***	.0187***
	[.0141, .0201]	[.0144, .0201]	[.0057, .0064]	[.0023, .0031]	[.0172, .0208]
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.4067	.3494	.0379	.0242	.0902
Nr. treated	0	0	0	0	0
Nr. matched units	3	3	3	3	3
Nr. unique controls	0	0	0	0	0
Nr. obs	99,464	99,464	99,464	99,464	99,464

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, marginal cost, markups and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $10\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from three matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, columns (3) and (4) for marginal cost $\left(MC^{kl}_{p,t}\right)$ and markup differences $\left(\mathcal{M}^{kl}_{p,t}\right)$ and column (5) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of nested CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.16: Geographic market segmentation: Robustness - Cutoff: 10% and Nr. controls: 1

Y	$P^{kl}_{p,t}$	$T^{kl}_{p,t}$	$L^{kl}_{p,t}$	$\Lambda^{kl}_{p,t}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	$.3304^{***}$	$.2486^{***}$	$.1403^{***}$	$.4252^{***}$
	$[.3012, .3794]$	$[.2196, .2813]$	$[.1389, .142]$	$[.3844, .4898]$
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.1559	.1308	.013	.0391
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				
$\hat{\gamma}_{Y,\varepsilon}$	$-.0029^{*}$	$-.0029^{**}$	$.0069^{***}$	$.0167^{***}$
	$[-.0072, .0008]$	$[-.0059, -.0004]$	$[.0066, .0073]$	$[.0136, .021]$
$\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}(0)\right]$	.274	.2183	.0253	.0822
Nr. treated	601	601	601	601
Nr. matched units	1	1	1	1
Nr. unique controls	98	98	98	98
Nr. obs	40,101	40,101	40,101	40,101

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $5\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from one matched domestic region pair. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, column (3) for price differences $\left(L^{kl}_{p,t}\right)$ and column (4) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.17: Geographic market segmentation: Robustness - Cutoff: 10% and Nr. controls: 2

Y	$P_{p,t}^{kl}$	$T_{p,t}^{kl}$	$L_{p,t}^{kl}$	$\Lambda_{p,t}^{kl}$
	(1)	(2)	(3)	(4)
EUROPE				
$\hat{\gamma}_{Y,\varepsilon}$	$.3465^{***}$	$.2553^{***}$	$.1403^{***}$	$.4259^{***}$
	$[.3137, .3971]$	$[.2265, .2923]$	$[.139, .1418]$	$[.3836, .4878]$
$\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}(0)\right]$	.1453	.1238	.013	.0362
Nr. treated	153	153	153	153
Nr. matched units	2	2	2	2
Nr. unique controls	106	106	106	106
Nr. obs	18,607	18,607	18,607	18,607
USA				
$\hat{\gamma}_{Y,\varepsilon}$	$.0051^{***}$	$.0025^{*}$	$.0068^{***}$	$.018^{***}$
	$[.0019, .0081]$	$[-.0001, .0051]$	$[.0065, .0072]$	$[.0147, .0229]$
$\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}(0)\right]$	.2666	.2133	.0255	.0812
Nr. treated	620	620	620	620
Nr. matched units	2	2	2	2
Nr. unique controls	109	109	109	109
Nr. obs	72,853	72,853	72,853	72,853

Notes: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $10\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from two matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P_{p,t}^{kl}\right)$, column (2) for taste differences $\left(T_{p,t}^{kl}\right)$, column (3) for price differences $\left(L_{p,t}^{kl}\right)$ and column (4) for product availability differences $\left(\Lambda_{p,t}^{kl}\right)$ computed under the assumption of CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}_{p,t}^{kl}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.

Table E.18: Geographic market segmentation: Robustness - Cutoff: 10% and Nr. controls: 3

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: This table presents the results of applying the matching estimator to cost-of-living, taste, price and cost-of-living differences for EU and US regions separately. To implement the estimator, we consider international region pairs within the $10\%^{th}$ percentile of the distribution of geographic differences and we construct the counterfactual from three matched domestic region pairs. Column (1) shows the results for cost-of-living differences $\left(P^{kl}_{p,t}\right)$, column (2) for taste differences $\left(T^{kl}_{p,t}\right)$, column (3) for price differences $\left(L^{kl}_{p,t}\right)$ and column (4) for product availability differences $\left(\Lambda^{kl}_{p,t}\right)$ computed under the assumption of CES preferences. We show provide the average absolute difference for the matched domestic region pairs $\left(\hat{\mathbb{E}}\left[\hat{Y}^{kl}_{p,t}\right]\right)$ alongside the estimates. We also provide the number of international region pairs that satisfy the cut-off condition, the number of domestic region pairs we use to construct the counterfactual and the total number of unique domestic international pairs we use to construct the counterfactual values. Finally, we provide the number of observations which also take into account the number of product categories and years that go into computing the estimate. Block-bootstrapped 5%-95% confidence intervals on 100 iterations. These are constructed as follows. We first draw with replacement households using population weights and elasticities of substitution from their empirical distributions. Given this sample of observed prices and quantities and the elasticities of substitution, we construct regional cost-of-living differences. Finally, these estimated regional cost-of-living differences are then used to construct an estimate of the differences in absolute values between international and domestic region pairs using the matching estimator. Reported significance levels are at the $p < 0.1^{*}$,$p < 0.05^{**}$ and $p < 0.01^{***}$ levels.