Evaluating the Impact of Online Market Integration-Evidence from the EU Portable PC Market

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Abstract

We develop a framework to evaluate the impact of market integration, accounting for spillovers between multiple distribution channels. Our adaptation of the standard random coefficients logit demand model allows for substitution between distribution channels and incorporates consumer arbitrage across countries. We apply our framework to the European portable PC market, where geo-blocking practices that restrict online cross-border trade have recently been banned. The distributional effects from the cross-country price convergence are substantial. Consumers in high income countries gain most, while consumers in medium and low income countries are only marginally better or even worse off. The total consumer and welfare gains from reducing cross-border arbitrage costs are more modest, and mainly due to increased product choice rather than reduced price discrimination.

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1 Introduction

Many consumer goods markets may remain nationally segmented, even without import tariffs because of important non-tariff barriers to trade. Such barriers are not only due to protective national government regulations. They can also be the result of deliberate strategies by firms to raise consumer cross-border trade costs, for example through distribution agreements that restrict retailers to sell in other countries. Free trade areas have taken various actions against firms that engage in such restrictive practices.[1] Policy makers that actively promote cross-border trade by consumers make the implicit presumption that full market integration would make markets more competitive to the benefit of all consumers. Economic theory, however, suggests that this is not so obvious. First, removing opportunities to engage in price discrimination may benefit consumers in some countries at the expense of consumers in other countries. Second, the impact on overall welfare is ambiguous, especially in the presence of oligopolistic behavior.

In this paper, we develop an empirical framework to assess the impact of reducing cross-border trade costs in nationally segmented markets. We are particularly interested in the situation where only one distribution channel (the online channel) becomes more integrated, while other channels (traditional "brick-and-mortar" channels) remain segmented.

We are inspired by a recent policy in 2018 of the European Commission, which put a ban on widespread geo-blocking practices. Such practices restrict consumers from purchasing products online in other countries. They were held responsible for the limited cross-border trade in online markets and for preventing the rise of a single European digital market. A ban on geo-blocking can thus make online markets more integrated, without directly affecting segmentation in the traditional distribution channel. In earlier investigations, the Commission indeed found that online cross-border shopping was very limited despite large cross-country price differences, notably in the markets for consumer electronics. For example, according to Eurostat in 2015 only 1.6 percent of consumers had ordered computer hardware from a different EU country. A mystery shopping survey carried out in 2015 on behalf of the European Commission found that 79 percent of cross-border shopping attempts for consumer electronics products were geo-blocked.

Our framework to assess the impact of reducing cross-border trade costs in online markets starts from a differentiated products demand model. We explicitly model the fact that consumers can purchase their products at two distribution channels: the traditional and the online channel. Furthermore, after integration consumers can purchase their products online in the other EU countries. We could in principle make use of the standard random coefficients logit demand model of Berry (1994) and Berry, Levinsohn and Pakes (1995; henceforth BLP). However, such an approach would not be warranted in our setting. It would involve a very high dimensional (type 1 extreme

[1] A well-known example is the automobile industry, with cases in both Europe and North-America on vertical restraints that were imposed by manufacturers on their dealers to restrict selling to customers in other countries.

value) individual taste term, that is not only specific to each product but also to the distribution channel and country of purchase where each product is available. This would lead to undesirable substitution patterns between the same products sold in different distribution channels and (after integration) in different countries. Even more importantly, it would lead to misleading welfare conclusions when enlarging the choice set to the same products sold online in other countries. To tackle these issues we develop an adapted BLP model similar to Song (2015), which in our context reduces the dimensionality of the individual taste term to only the product, rather than the product, channel and country of purchase. We show how to accurately approximate this adapted BLP model by a random coefficients nested logit model, where each product constitutes a nest and channels/countries are elemental alternatives within each product nest. In contrast with other random coefficients nested logit models (e.g. Goldberg and Verboven, 2001), the nesting parameter is not estimated but rather set at a value close to 1 to approximately eliminate artificial differentiation between the same products sold through a different channel (or country after integration). Our approach relates to the pure characteristics model of Berry and Pakes (2007), but is easier to estimate with multiple random coefficients.[2]

We apply our analysis to the market for portable PCs in 10 EU countries during 2012-2015, a period where there was strong national market segmentation because of the geo-blocking practices. Our preliminary evidence shows that international price differences for identical products were large, leaving substantial scope for online consumer arbitrage. In fact, in more than half of the cases the lowest online prices prevailed in the low-income countries Poland and Slovakia, while the highest prices were more frequent in high-income countries such as Belgium, Denmark and the Netherlands. We then estimate our adapted BLP demand model in the presence of national market segmentation. Consistent with the documented price differences, we find that consumers are most price sensitive in the group of low-income countries, while consumers are the least price sensitive in the high-income countries. We also find that there is substantial heterogeneity in the valuation for the online distribution channel. This implies that there is only moderate substitution between both distribution channels (though considerably more than in a standard BLP model with consumer heterogeneity that is specific to both the product and the channel).

After adding a supply side with oligopolistic price-setting behavior, we evaluate the impact of a ban on the geo-blocking restrictions. The ban makes online markets integrated as it enables consumers to purchase online in other countries (possibly at an extra shipping cost). The ban can have both direct effects on prices in the online channel, and possibly indirect effects in the traditional channel (through substitution between channels). We decompose the policy's impact into two main components: a price convergence and a choice expansion effect. The first effect

[2] Berry and Pakes (2007) entirely eliminate the logit error term, whereas we reduce its dimensionality from the product/channel/country level to the product level. Song (2007) and Nosko (2011) estimate a pure characteristics model with two random coefficients, both applied to the CPU market.

assumes that consumers can make cross-border purchases only for products that were previously already available in their own country. This effect focuses on consumer arbitrage and how it induces product-level price convergence and eliminates third-degree price discrimination (based on the consumer's country of residence). The second effect assumes that consumers can also make cross-border purchases for products that were not available in their own country before the ban. This effect incorporates how consumers may benefit from increased product availability.

Our main findings can be summarized as follows. First, we find substantial distributional effects of the policy on consumers and firms. Online prices drop by on average 1.5 percent in high-income countries, while they increase by on average 7.9 percent in medium- and by 12 percent in low-income countries. This indicates a redistribution from consumers in low-income to high-income countries because of the price convergence effect. However, the choice expansion effect counterbalances this because more products become available online. As such, consumer welfare in low-income countries remains roughly unchanged, while consumer welfare in high-income countries increases even more strongly after taking into account expanding product availability. Total firm profits remain essentially unchanged.

Second, we evaluate the total EU effects of integrating online markets. We find that a ban on geo-blocking has only small effects on total EU consumer surplus and welfare if it does not lead to more product choice. In other words, the price convergence effect that reduces price discrimination only redistributes between different countries. However, the ban implies sizable total consumer benefits after taking into account the product choice expansion effect, with gains of about 300 million Euro in the portable PC market. The spillover effects of online market integration to the traditional channel turn out to be small, because of substantial heterogeneity in the valuation of online, which implies that most consumers stay with their own preferred channel. We also show that consumer benefits further increase in the future as e-commerce (20 percent during our sample period) continues to gain in popularity. Furthermore, the geo-blocking ban applies to a wide range of retail categories, so that the total effects can add up to even more substantial amounts.

These findings are based on our adapted BLP model, which eliminates the artificial individual taste valuations for the channel and country-of-purchase of every product. We show that a standard BLP model that includes such idiosyncratic valuations would lead to misleading conclusions because it mechanically includes gains from additional variety that is specifc to each product, distribution channel and country-of-purchase. First, this would substantially overestimate the effects on consumer welfare. Second, this would also imply that firms would actually greatly benefit from opening up online markets across the EU. Such a prediction is at odds with a simple revealed preference argument, as firms deliberately chose to impose cross-border trade restrictions to segment online markets and did not support the geo-blocking ban.

Our paper contributes to several strands of literature. First, we contribute to the literature on international price differences and the law of one price in imperfectly competitive markets.[3] This literature has made various advances in understanding the sources of international price differences (local costs versus markups), e.g. Goldberg and Verboven (2001) for cars; Kanavos and Font (2005) for pharmaceuticals; Gopinath, Gourinchas, Hsieh and Li (2012) for a grocery chain; and Goldberg and Hellerstein (2013) for beer. However, there has been limited attention to the role of cross-border trade costs in obtaining market integration, and the implied welfare effects. Our contribution to this literature is to provide a framework for empirically evaluating the impact of a reduction (or entire removal) of cross-border trade costs on international price differences and welfare. This is distinct from interesting recent work by Dubois, Gandhi and Vasserman (2019), who consider how direct price regulations may affect price differences between countries without involving cross-border trade.

Second, we contribute to a recent literature on international price differences in online markets. Most work has focused on traditional, brick-and-mortar sales channels, and only a few contributions document international price differences in online markets, e.g. Gorodnichenko and Talavera (2017) for a range of electronic products sold in the US and Canada, Duch-Brown and Martens (2014) for household appliances and Duch-Brown, Grzybowski, Romahn and Verboven (2021) for various electronic products sold in the European Union.[4] We contribute to this literature by going beyond a descriptive analysis and in particular show how our framework can be used to evaluate the indirect spillover effects of a reduction in cross-border trade costs in one distribution channel on international price differences in another distribution channel.

Third, we contribute to a literature on the impact of online variety on welfare. In an influential paper, Brynjolfsson, Hu and Smith (2003) quantify the consumer gains from online variety to be seven to ten times larger than the gains from competitive price effects. Quan and William (2018) revisit the gains from variety by accounting for the role of local tastes. Ackerberg and Rysman (2005) show how logit models may overestimate the welfare gains by adding a new dimension of differentiation with any new product. We suggest an adapted BLP model with an individual taste term that is common across channels/countries of the same product, avoiding artificial extra differentiation which would overestimate the welfare gains from online variety. The adapted BLP model closely relates to Song (2015), who imposes the individual taste term to be common to products of the same brand.[5] His setting does not allow him to estimate multiple random coefficients, and appears to be computationally cumbersome (for example requiring a very large number of simula-

[3] Early work started at the aggregate level with Frankel and Rose (1996) and Obstfeld and Rogoff (2000).

[4] The literature on e-commerce has focused almost exclusively on price dispersion at the national level, showing that online markets do not exhibit smaller price dispersion than online markets, see e.g. Pan et al. (2004) for a review of the early literature on this topic.

[5] Marshall (2015) and Grubb and Osborne (2015) provide related applications with common taste terms, using a simulated maximum likelihood framework (which does not require inverting the market share system). Thomassen (2017) suggests an approach where not only the individual taste parameter is imposed to be common to all engine variants of the same car model, but also the different variants' unobserved characteristics are forced to be equal.

tion draws). Our approach overcomes these difficulties by approximating the adapted BLP model with a limiting version of a random coefficients nested logit model. We show that for a nesting parameter that is imposed to be sufficiently close to one, the approximation becomes very accurate (i.e. close to the true adapted BLP model).

The remainder of the paper is organized as follows. Section 2 describes the relevant institutional background on cross-country trade restrictions and geo-blocking, and provides preliminary evidence on the scope for arbitrage in the portable PC market. Section 3 provides a general overview on how to model demand in segmented versus integrated markets. Section 4 presents our model and empirical findings on substitution patterns and competition under segmented markets. Section 5 develops our counterfactual approach and discusses our findings of the impact of introducing online market integration. Section 6 concludes.

2 Institutional Background and Data

We first provide a brief description of policies to integrate markets in Europe, and the recent ban on geo-blocking practices. Next, we describe our dataset on the market for portable PCs. Finally, we provide some key information relevant for our empirical analysis.

2.1 Cross-country Trade Restrictions and Geo-blocking

One of the cornerstones of the European single market is the achievement of free movement of goods (the other ones being free movement of capital, services and labor). After removing all import tariff barriers to create a single customs union, the European Union focused on reducing a large number of non-tariff trade barriers. Part of these efforts focused on forcing national countries to take steps to harmonize their national legislations, which often implicitly created obstacles to cross-border trade (e.g. differing national product requirements). At the same time, the European Commission has taken numerous actions against private firms for anti-competitive practices that prevented cross-border sales through export restrictions. This has resulted in large fines in many competition cases, including major companies in a variety of industries, such as automobiles (including the 102 million euro fine to Volkswagen in 1998 and the 72 million euro fine to DaimlerChrysler in 2001, beer (with the 200 million euro fine to AB Inbev in 2019) and card payments (fine of 570 million euro to Mastercard in 2019). With the rise of e-commerce, cases also emerged against companies preventing cross-border online shopping, as illustrated by the 40 million euro fine to clothing company Guess in 2018 for preventing consumers to shop online in other countries. The restrictive trade practices by private companies have often prompted the Commission to conduct sector-wide investigations to arrive at guidelines or binding regulations.

Against this background, the European Commission (2017) published a report on the e-commerce sector inquiry in 2017, as part of its broader goal of achieving a Digital Single Market. The investigation highlights that manufacturers increasingly make use of: (i) own online shops, (ii) selective distribution to control their distributors, and (iii) various contractual restrictions to control distributors. The Commission showed a particular concern with the widespread use of geoblocking practices. Geoblocking practices are actions taken by manufacturers or retailers to restrict cross-border online trade. Based on the visitor's IP adddress, firms can block consumers from access to foreign websites, they can re-route them to the local version of the same online store, or simply refuse to deliver cross-border or refuse payment from a foreign bank. In a Mystery Shopping Survey carried out by GfK, the European Commission (2016) indeed found that geo-blocking was very common in the markets for consumer electronics. It found that 79 percent of cross-border shopping attempts for consumer electronic products were geoblocked.[6]

To overcome these cross-border frictions in the online distribution channel and as part of its Single Digital Market strategy, the European Council adopted a new regulation 2018/302 that bans unjustified geoblocking within the EU internal market; see EU Regulation (2018). The regulation became effective on 3 December 2018 and expressly forbids that a consumer located in one Member State is blocked from ordering a product in an online store located in any other Member State.

2.2 Data

We use a panel dataset from GfK for the market of portable computers, with monthly information for 10 EU countries at the product level. Our monthly data cover the period between January 2012 and March 2015. The 10 EU countries are: Belgium, Denmark, France, Germany, Italy, the Netherlands, Poland, Slovakia, Spain, and the United Kingdom. Taken together, this covers 78 percent of the population and 84 percent of GDP in the EU in 2015. The product-level data consist of sales, prices and various product characteristics, broken down by two distribution channels: the traditional or "brick-and-mortar" channel and the online channel.[7] GfK collected

[6]The GfK Mystery Shopping Survey collected in total 10,537 observations for cross-border online shopping attempts for 147 different country pairs. From each EU country, between 200 and 600 shopping attempts were tested, depending on the relative importance of the country in total (estimated) on-line cross-border trade in the EU. The country pairs were chosen primarily to represent the major online trade routes within the EU28. Mystery shoppers were assigned a website and two products. First, they tested the website and the availability of the two products as a domestic shopper in the country of establishment of the webshop. Via a VPN network, they accessed the targeted webshop with a domestic IP address of the shop's country and recorded the information on the availability of the assigned products, the price, delivery costs and payment options. Then the IP address was changed to the country of residence of the buyer to test whether a cross-border shopping attempt could be completed successfully. From this foreign IP address, the mystery shoppers put the assigned product into the shopping basket and performed all steps to complete the order.

[7]GfK uses a "point of sales tracking" technology, which reports which products are sold, when, where and for how much, both at online and offline outlets on monthly (or sometimes weekly) basis. The data was collected directly from the electronic point of sales systems from retailers and resellers. Sales were tracked at the individual stock keeping unit level and coded with a full set of features using a cohesive international methodology to allow for accurate comparison both within and across European markets. Any brand or model which was found to be sold in the covered countries is tracked, unless the brand is exclusive, in which case it is still audited but with a label which hides its exact origin. Sales volumes and turnover per item were gathered at the same time as the model specification information. The price of the item was calculated as turnover divided by units sold.

this information from a comprehensive sample of retailers, covering 87 percent of total portable PC sales in these countries. A limitation of our analysis is that the available data are aggregated across retailers within each country (similar to other work on the PC market).[8] We can therefore not distinguish between the underlying manufacturers' and retailers' pricing strategies. We further motivate and discuss our approach here and in Section 4.4 on oligopoly pricing, based on more detailed background industry information in online Appendix A.1.

Each portable PC or "product" is described by three identifiers: (i) the brand, such as Dell or Sony; (ii) the series, such as Inspiron or Latitude in the case of Dell, and (iii) the model, such as E3330 or E6520 in the case of Dell Latitude. An observation in our panel dataset is thus a product (brand-series-model), distribution channel (traditional or online), country and period (month). The initial data set includes 931,509 observations. We aggregate sales for duplicated products and for products with variations in model code, which is caused by different coding conventions between countries or minor differences in product attributes, such as the color of the chassis. In the example above, we aggregate sales for models Dell Latitude E3330 and Dell Latitude E6520, as well as other models belong to the Latitude series. To reduce the computational burden of the estimation and because variation in market shares is limited within quarters, we limit the months in our sample to February, May, August and November. As an alternative, we also aggregated data at the quarterly level. Moreover, we remove observations with very small market shares, such that 1.5 percent of total units sold are dropped. To exclude low-priced laptops that are primarily designed for web browsing only, we censor the price distribution at 400 euros. During the sample period it is also very unusual for a laptop to be sold at a price of more than 2,000 euros, and we drop these "high-end" observations. Note that these low-end and high-end products are also purchased less frequently. The final data set consists of 10,288 observations on products, distribution channels, countries and periods. The number of unique products across channels, countries and months in the entire sample is 186. [9]

For each observation, we have the quantity sold, price and several observable characteristics: the included CPU's speed, the amount of RAM, the laptop's weight, its outer diagonal and its display resolution. As we do not observe the display diagonal for all the models in our data set, we infer the diagonal from each laptop's outer measurements. Moreover, we compute the display resolution from this inferred display diagonal. This is very close to the reported numbers for observations where we do have information (with a slight overstatement for all products).

[8]The underlying data cover the following types of retailers: system houses, office equipment retailers, computer shops, consumer electronics stores, mass merchandisers, pure internet players, mail orders/online catalogues. It does not include: duty free shops, gas stations, door to door, street markets, discounter stores and direct sales (to staff, hotels, schools, hospitals, etc.). The sample is representative both for the smaller independent sellers as well as for the large chain-stores.

[9]This seems to be broadly in line with other studies on the PC market (which include portables and desktops). We also considered a more disaggregate product definition based on model names (e.g. Dell Latitude E3330 or E6520), which results in 48,696 observations. This approach appears less desirable to us because of the large number of unique yet similar products (2,783), often with a short time span or country coverage.

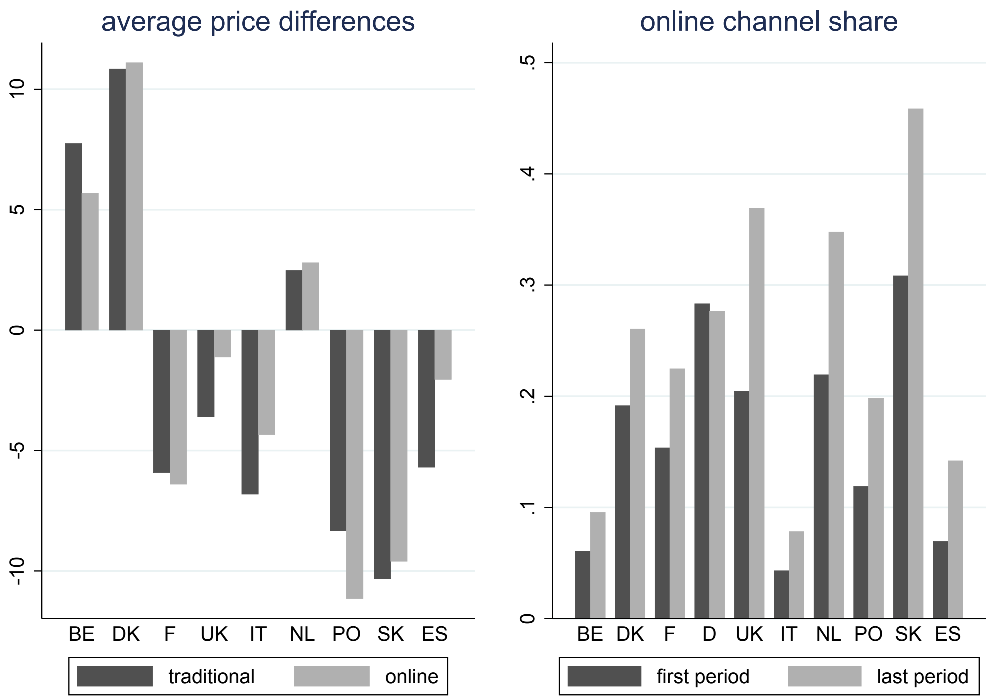
Table 1: Quantities, Prices and Product Characteristics

	min	10^{th} percentile	median	mean	90^{th} percentile	max
$q_{j,\text{trad}}$	0	83.4	2 262	12 530	39 541	186 603
$q_{j,\text{on}}$	0	0	694	3 500	9 882	47 144
Price (all products, euro)	400	463	675	774	1198	1999
Price (traditional, euro)	400	468	652	752	1 147	1 973
Price (online, euro)	400	466	662	759	1 170	1 999
CPU speed (GHz)	1.03	2.08	2.55	2.57	3.13	3.67
RAM (GB)	2	4	6	6.77	8	16
Weight (kg)	0.58	1.29	2.31	2.17	2.72	4.68
Diagonal (inch)	10.9	15.1	17.5	17	18.4	20.5
Display Resolution (ppi)	74	85	94	101	124	217
J	24	33	49	50	66.5	85
J_{trad}	24	32	46.5	47.1	62.5	76
J_{on}	8	15	31	32.0	50.5	68

Note: Based on 10 288 observations. The distributional information for product-level units sold in the two distribution channels, $q_{j,\text{trad}}$ and $q_{j,\text{on}}$, is based on summing each laptop model's unit sales between countries for each date in the sample. Price is measured in euros; price per channel (traditional or online) refers to products that are available in both the online and offline distribution channel. CPU speed and RAM are respectively measured in gigahertz and gigabyte. Weight is measured in kilograms. The diagonal is measured in inches and is based on the outer dimensions of each laptop's body, which gives us measures that are larger than the actual display diagonal. Display resolution is measured in pixels per inch and we use the inferred display diagonal to compute this quantity, so that all resolutions are lower than the actual display resolution.

Table 1 presents summary statistics for these variables. The average sales of a portable PC is 12,530 in the traditional channel, compared with 3,500 in the online channel. Median sales are considerably lower, indicating a skewed distribution of sales towards a more limited number of top selling models. Minimum sales are zero; these are products sold at only one channel. The average price of a portable PC is 774 euro. This is comparable at both distribution channels: 752 euro at the traditional channel and 759 at the online channel for the subset of products available at both channels (see Duch-Brown, Grzybowski, Romahn and Verboven (2021) for more detailed evidence on this). The large variation in prices stems in part from a considerable variation in the product characteristics, but also from variation across countries and over time. The final rows show the number of products by market (J) and by channel and market (J_{trad} and J_{on}). The majority of products tend to be more widely available in the traditional brick and mortar stores than through the online channel. For example, the median number of products in a given market is 49 overall: 46.5 at the traditional channel and only 31 at the online channel. This may seem to suggest there is less variety in the online channel, in contrast with other markets such as books (e.g. Brynjolfsson, Hu and Smith, 2003). Note however that there is still a large number of brick-and-mortar stores (which may individually offer less variety than online stores). Furthermore, many products may be

Figure 1: Online Market Shares and Online Average Price Differences Relative to Germany



Note: The left panel shows quality-adjusted price differences relative to Germany, based on a hedonic regression as explained in the text. The right panel shows the share of unit sales accounted for by the online distribution channel. The countries are coded as follows: Belgium (BE), Denmark (DK), France (F), Germany (D), United Kingdom (UK), Italy (IT), the Netherlands (NL), Poland (PO), Slovakia (SK), and Spain (ES).

listed online but not actually be sold. This is supported by a report from Ecorys (2011), according to which the online sales channel mainly focuses on more popular products also available through traditional stores.

2.3 The Scope for Cross-Border Arbitrage

While we study demand and pricing in both retail channels, our main interest is in the online channel. The right panel of Figure 1 shows the market shares of the online channel for portable PC sales in the various countries of our analysis, for the first and last month of our data set (January 2012 and March 2015). There are substantial cross-country differences in the popularity of online. The online market share exceeds 25 percent in Denmark, Germany, the Netherlands and Slovakia near the end of our sample period, while it is still relatively limited in Belgium, Italy and Spain. The online share tends to be growing in most countries. A notable exception here is Germany, which already started at a higher online share.

The left panel of Figure 1 shows that there are considerable price differences for portable PCs across countries, taking Germany as the base.[10] Interestingly, this is not only the case at the traditional sales channel (where one may expect cross-border shopping to be more difficult), but also at the online channel. Belgium and especially Denmark are on average more expensive, while most notably the Eastern European countries Poland and Slovakia tend to be less expensive. Note that these cross-country price differences tend to be persistent over time, as shown in detail for a larger set of consumer electronics categories by Duch-Brown, Grzybowski, Romahn and Verboven (2021).

These average price differences show a relationship with per capita median income levels. As shown in Figure A.1 of online Appendix A.2, countries can be divided into three groups: low income (Poland and Slovakia), medium income (Spain and Italy) and high income (the other countries). As we are interested in understanding the sources of price differences before assessing the impact of removing cross-country trade costs, we allow for differences in price sensitivities across these country groups in our empirical analysis.

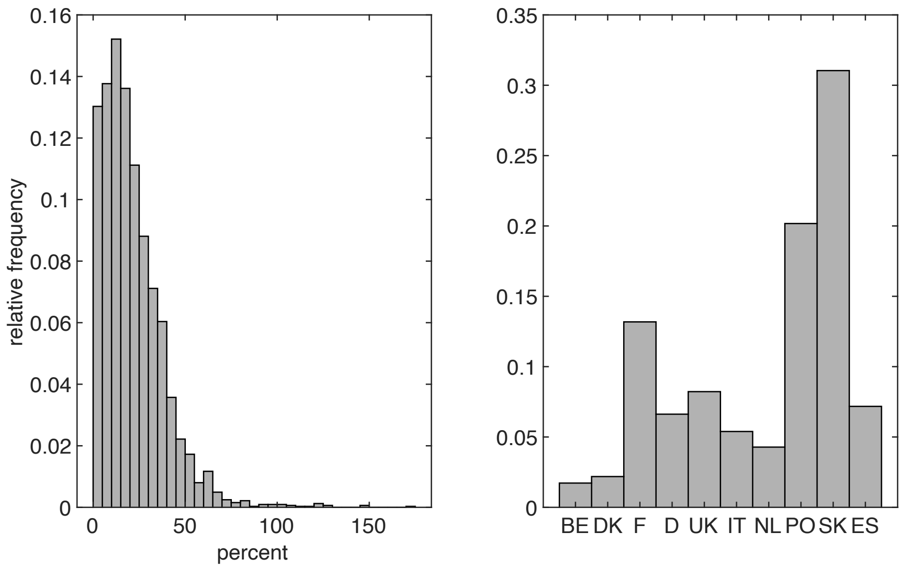
The cross-country price differences give an indication of the average consumer benefits from shopping abroad. To show the full scope of cross-border arbitrage possibilities, we implement the following exercise. For each product sold in the online channel and each time period, we determine the lowest available price and compute the percentage price differences between all other online prices for the same product and that minimum price. The left panel of Figure 2 plots the distribution of these relative price differences across products, while the right panel shows the frequency at which each country's online channel contains the lowest price.

The mean and median relative price differences are respectively 21.5 and 17.8 percent. With an average price for a portable PC close to 800 euros, this indicates potential monetary savings of on average 166 euros. As even higher price differences are common, this emphasizes that consumers have a strong incentive to purchase their preferred laptop model abroad. Of course, if a ban on the geoblocking practices would make this feasible, firms may respond by adjusting the cross-country price differences, which is the focus of our counterfactual analysis.

The right panel of Figure 2 shows which countries' online channels tend to offer the lowest prices. Not surprisingly, Poland and Slovakia, which have the lowest average prices and also make up the low-income group, are the lowest price countries for more than half of the products, so the incentives to shop online in these countries are strongest. This underlines that these low-income countries also tend to have access to the lowest prices when firms price to market within national borders. With the exception of France, all other high-income countries account for a very small share of the minimum online price observations. This is again consistent with firms implementing

[10]This figure reports country-channel percentage price differences, obtained from a regression of price on product fixed effects, a time trend, various product characteristics and a set of dummy variables for country and distribution channels. They can be interpreted as quality-adjusted price differences. Price differences are comparable without the quality adjustment, indicating that changes in product characteristics are comparable across countries.

Figure 2: Relative Online Price Difference to Minimum Price Observation at the Product-Level



Note: For each available online product and period, the percentage price difference in a country relative to the cheapest country is computed. The left panel shows the distribution of these price differences. The right panel shows the frequency with which each country's online channel contains that minimum price.

price discrimination between populations that have different price sensitivities.

The computed percentage price differences between the cheapest and the most expensive country conceal the fact that some products may be widely available, while other products may be available in only a few countries. From the perspective of consumers, this offers a new reason to shop online: take advantage of increased variety in other countries, rather than only a reduced price for products already available in their country of residence. To shed light on this, Table 2 provides an overview of the products available online in the various countries in at least one period. As shown in the last column, online coverage indeed varies across countries, with the highest level in Denmark and Germany and the lowest level in Belgium and Italy. Since the seven largest brands are present in all countries (with a market share of 78 percent during our sample), differences in coverage mainly relate to the smaller brands. This may be due to some prominent foreign retailers. According to the other columns, the average product characteristics are quite comparable across countries. The EU averages are slightly lower, indicating that the commonly available products tend to have slightly higher characteristics. Overall, a ban on geo-blocking practices would mainly imply increased variety, without major changes in average available quality. In our counterfactual analysis, we will take into account how a geo-blocking ban may also affect welfare through such expanded product choice set (apart from offering arbitrage opportunities on products consumers can already purchase at home).

Table 2: Average Product Characteristics per Country

	CPU speed	RAM	Weight	Diagonal	Resolution	Price	N
BE	2.63	7.53	2.38	17.46	100	863	62
DK	2.50	6.40	2.13	16.83	102	885	107
F	2.54	6.96	2.29	17.27	101	729	77
D	2.55	6.34	2.16	16.99	102	813	108
UK	2.42	6.01	2.12	16.74	101	754	87
IT	2.45	6.26	2.24	17.25	96	648	42
NL	2.61	7.02	2.24	17.11	104	863	96
PO	2.63	7.15	2.30	17.31	102	716	74
SK	2.55	6.69	2.21	16.95	102	743	90
ES	2.57	6.64	2.28	17.27	98	740	61
All	2.49	6.03	2.16	16.93	101	813	151

Note: The table shows the average product characteristics and number of unique products available online in each country in at least one period in our data. The countries are coded as follows: Belgium (BE), Denmark (DK), France (F), Germany (D), United Kingdom (UK), Italy (IT), the Netherlands (NL), Poland (PO), Slovakia (SK), and Spain (ES).

3 Modelling Demand in Segmented versus Integrated Markets

Before describing the demand and oligopoly model in detail in the next sections, it is instructive to start with a general outline on how to model consumer demand in segmented and integrated markets. We first show how to implement this through the workhorse differentiated products demand model of BLP. Next, we discuss the critical shortcomings with this approach in our setting. This motivates our adapted BLP demand model, and provides a roadmap of the various parts of our analysis in the next sections.

A consumer i located in a country $c \in C$ faces the choice to buy a certain product j at a distribution channel $k \in \{T, O\}$ in a (possibly different) country $d \in C$. The channel $k = T$ refers to the traditional (or offline) channel; the channel $k = O$ refers to the online channel. The set of available products in country c at distributional channel k is $\mathcal{J}_{c,k}$. A consumer may also choose the outside good, which we define as product $j = 0$ in the consumer's own country c.

Under segmented markets, a consumer located in country c can buy products only in her own country c, so her choice set consists of $\mathcal{J}_{c,T} \cup \mathcal{J}_{c,O}$. With integrated markets, a consumer in country c can engage in cross-border trade, and hence sees her choice set enlarged to include those of other countries. For example, if integration implies that products become available across all countries through both distribution channels, then the (common) choice set to all consumers becomes $(\cup_{d\in C}\mathcal{J}_{d,T}) \cup (\cup_{d\in C}\mathcal{J}_{d,O})$. If integration implies that products become available across all countries only through the online distribution channel (as with a ban on geo-blocking), then the choice set of a consumer located in country c becomes $\mathcal{J}_{c,T} \cup (\cup_{d \in C} \mathcal{J}_{d,O})$.

The conditional indirect utility of consumer i located in country c for a product j purchased at channel k in country d is:

$$u_{ic,jkd} = \underbrace{x_j \beta_i + \gamma_i \times \mathbf{1}(k = O) - \alpha_c p_{jkd} + \xi_{c,jk}}_{V_{ic,jkd}} + \varepsilon_{ic,jkd}. \tag{1}$$

The vector x_j consists of product characteristics (identical across channels and countries), $\mathbf{1}(k = O)$ is an indicator equal to one for the online channel, p_{jkd} is the price of product j at channel k in country of purchase d, $\xi_{c,jk}$ is the unobserved quality of product j at channel k, as perceived by consumers located in country c. The parameters β_i and γ_i are random taste parameters for the valuation of the product characteristics and the online distribution channel, and α_c is a country-specific price parameter. Finally, the random term $\varepsilon_{ic,jkd}$ is an individual-specific valuation of consumer i located in country c for product j purchased at distribution channel k in country d, i.i.d. distributed according to a type 1 extreme value distribution. We will sometimes write utility excluding the individual-specific valuation term as $V_{ic,jkd} \equiv u_{ic,jkd} - \varepsilon_{ic,jkd}$. We normalize this term to zero for the outside good, $V_{ic,0Tc} = 0$.

Under geographically segmented markets, a consumer i can buy only in her own country c, and not in any other country $d \neq c$. Assuming random utility maximization and integrating over the random taste parameters β_i and γ_i, we can write the market share for product j at channel k in country c as:

$$s_{c,jk} = s_{c,jkc} = \int \frac{\exp\left(V_{c,jkc}(\beta, \gamma)\right)}{1 + \sum\limits_{j' \in \mathcal{J}_{kc}} \sum\limits_{k' \in \{T,O\}} \exp\left(V_{c,j'k'c}(\beta, \gamma)\right)} dF_{\beta\gamma}(\beta, \gamma). \tag{2}$$

The first equality highlights that a product's market share in country c is just equal to the market share of consumers located in that country, because consumers cannot buy in any other country $d \neq c$, i.e. $s_{c,jkd} = 0$ for $d \neq c$. The second equality is the usual BLP expression for market shares in segmented markets, which averages the logit choice probabilities over unobserved consumer types (β_i, γ_i). Total demand by all L_c consumers located in country c for product j at channel k is $q_{c,jk} = s_{c,jk} L_c$.

With integrated markets, the choice set of a consumer located in country c includes all countries. The market share from consumers located in country c for product j at channel k in country d is then equal to:

$$s_{c,jkd} = \int \frac{\exp\left(V_{c,jkd}(\beta, \gamma)\right)}{1 + \sum\limits_{j' \in \mathcal{J}_{k'd'}} \sum\limits_{k' \in \{T,O\}} \sum\limits_{d' \in C} \exp\left(V_{c,j'k'd'}(\beta, \gamma)\right)} dF_{\beta\gamma}(\beta, \gamma). \tag{3}$$

Total demand by all consumers L_c located in country c for product j at channel k is $q_{c,jk} = \sum_d s_{c,jkd} L_c$.

Our general goal is to estimate a demand model under segmented markets (as in (2)), add an oligopoly model of price-setting behavior, and perform counterfactuals on how equilibrium changes under integrated markets (as in (3)). However, applying the standard BLP demand models, (2) and (3), is unsatisfying in our context because it is based on the very high dimensional i.i.d. individual taste term $\varepsilon_{ic,jkd}$. This term is not only specific to each product j, but also to each distribution channel k and each country of purchase d. This may imply implausible substitution patterns and misleading welfare implications when studying the impact of new goods that become available in other countries or distribution channels (as these would artificially increase the product space). Berry and Pakes (2007) develop an approach to eliminate the individual taste parameter and estimate a "pure characteristics" model by entirely eliminating the term $\varepsilon_{ic,jkd}$. However, their approach involves a considerable increase in computational complexity, and most applications use the standard BLP model (while being cautious to specify a sufficiently rich model to capture heterogeneity in the valuations of the product characteristics).

We instead propose an adapted BLP demand model, and specify utility as

$$u_{ic,jkd} = x_j \beta_i + \gamma_i \times \mathbf{1}(k = O) - \alpha_c p_{jkd} + \xi_{c,jk} + \varepsilon_{ic,j}. \tag{4}$$

This reduces the dimensionality of the individual taste parameter from $\varepsilon_{ic,jkd}$ to $\varepsilon_{ic,j}$: this is still specific to the product j, but no longer to the distribution channel k and country of purchase d. Hence, substitution patterns and welfare gains from increased product availability are not affected by artificial tastes for products at certain channels or countries of purchase. For our empirical demand analysis (section 4), only the elimination of the channel dimension is relevant, because we estimate the model under the assumption of segmented markets. For our counterfactual analysis (section 5), the elimination of the country of purchase dimension also becomes highly relevant, because it avoids attributing the gains from being able to purchase the same goods abroad to increased "variety".

4 Demand and Oligopoly in Segmented Markets

In this section, we analyze demand and oligopoly under segmented markets, i.e. when firms could use geo-blocking to prevent consumers from shopping online in other countries.

4.1 Adapted BLP Demand Model

We formulate a static demand model in line with other literature on the PC or smartphone industry, e.g. Sovinsky Goeree (2008), Eizenberg (2014), Song (2015), and Fan and Yang (2020). This enables us to focus on the dimensionality issue of the individual taste term in a typical BLP setting. In future research, it would be interesting to explore how to further extend this in the dynamic demand framework of Gowrisankaran and Rysman (2012).

Under segmented markets, a consumer located in country c can only purchase products in her own country c and not in any other country $d \neq c$. To simplify notation, we suppress the subscripts c in this subsection. The utility of consumer i for product j at channel k, (4), can be simplified to

$$u_{i,jk} = \underbrace{x_j \beta_i + \gamma_i \times \mathbf{1}(k = O) - \alpha p_{jk} + \xi_{jk}}_{V_{i,jk}} + \varepsilon_{i,j}. \tag{5}$$

Specify the online taste parameter as $\gamma_i = \gamma^O + \sigma^O \nu_i^O$, where γ^O is the mean valuation for shopping online (possibly negative), σ^O is the standard deviation, and $\nu_i^O \sim N(0,1)$ is a standard normal random variable. At this point, we do not yet specify the taste parameter for the product characteristics β_i. The key feature of this adapted BLP demand specification is that the individual taste parameter $\varepsilon_{i,j}$ is specific only to the product j, while in the standard BLP model it is specific to every alternative, i.e. every product j at every channel k (with a term $\varepsilon_{i,jk}$). In this subsection we discuss how this specification results in an aggregate market share system. In the next subsection and online Appendix A.3, we show how it can be approximated for estimation purposes through a random coefficients nested logit model, where each product is a separate nest (containing the traditional and online channel of each product as elemental alternatives).

A consumer chooses among all possible alternatives, but can conceptually break her choice problem down in two parts: determine the preferred sales channel for each product j, and then compare the preferred sales channel of every product across all possible products. The first part is simple: a consumer prefers the traditional channel T of product j if

$$u_{i,jT} \geq u_{i,jO},$$

or equivalently if

$$\nu_i^O \leq \frac{-\alpha \left(p_{jT} - p_{jO}\right) + \xi_{jT} - \xi_{jO} - \gamma^O}{\sigma^O} \equiv \Delta_j$$

(after substituting (5) and making use of $\gamma_i = \gamma^O + \sigma^O \nu_i^O$). Hence, a consumer prefers the traditional channel of product j if and only if her valuation for the online channel is sufficiently low, $\nu_i^O \leq \Delta_j$. Note that the cut-off value Δ_j depends only on the price and unobserved quality difference, and not on the product characteristics, as these are the same on both channels.

The second part of the consumer's choice problem compares the preferred channel of each product across all products. Suppose (without loss of generality) that the product cut-off values can be ranked as follows $\Delta_1 \leq ...\Delta_{j-1} \leq \Delta_j \leq \Delta_{j+1} \leq ... \leq \Delta_J$, i.e. product 1 is the least attractive at the traditional channel, whereas product J is the most attractive at the traditional

Table 3: Consideration Sets for the Adapted BLP Model

online valuation	$\mathcal{J}_T^j$	$\mathcal{J}_O^j$	$D_{i,j}$
$\nu_i^O \in [-\infty, \Delta_1)$	$\{1, 2, ..., J\}$	$\varnothing$	$\sum_{j' \in \mathcal{J}_T} \exp\left(V_{i,j'T}\right)$
$\nu_i^O \in [\Delta_1, \Delta_2)$	$\{2, ..., J\}$	$\{1\}$	$\sum_{j' \in \mathcal{J}_T^2} \exp\left(V_{i,j'T}\right) + \exp\left(V_{i,1O}\right)$
$\vdots$	$\vdots$	$\vdots$	
$\nu_i^O \in [\Delta_{j-1}, \Delta_j)$	$\{j, ..., J\}$	$\{1, 2, ..., j-1\}$	$\sum_{j' \in \mathcal{J}_T^j} \exp\left(V_{i,j'T}\right) + \sum_{j' \in \mathcal{J}_O^j} \exp\left(V_{i,j'O}\right)$
$\vdots$			
$\nu_i^O \in [\Delta_J, \infty)$	$\varnothing$	$\{1, 2, ..., J\}$	$\sum_{j' \in \mathcal{J}_O^J} \exp\left(V_{i,j'O}\right)$

Note: Consumers choose among all possible alternatives. Hence, their consideration sets are endogenous, i.e. a mental simplification of the entire choice set to one channel per product.

channel. Given this ordering, define the sets $\mathcal{J}_T^j \subseteq \mathcal{J}_T = \{j, ..., J\}$ and $\mathcal{J}_O^j \subseteq \mathcal{J}_O = \{1, ..., j-1\}$. Table 2 uses this notation to show the (endogenous) considerations sets of a consumer for different realizations of her online valuation ν_i^O.[11] For example, if $\nu_i^O \leq \Delta_J$, a consumer chooses to consider only products at the traditional sales channel. If $\nu_i^O \in [\Delta_1, \Delta_2)$, she chooses to compare product 1 of the online channel with the other products $j = 2, ..., J$ at the traditional channel. If $\nu_i^O \in [\Delta_{j-1}, \Delta_j)$, she compares products $1, 2, ..., j-1$ at the online channel with the remaining products $j, ..., J$ at the traditional channel. Finally, for $\nu_i^O \in [\Delta_J, \infty)$, she compares only products at the online sales channel.

Given these consideration sets, we obtain the following probabilities that a consumer would choose product j at the traditional channel T or online channel O:

$$s_{jT}(\beta_i) = \int_{-\infty}^{\Delta_1} \frac{\exp\left(V_{i,jT}\right)}{1 + D_{i,1}} d\Phi(\nu^O) + \int_{\Delta_1}^{\Delta_2} \frac{\exp\left(V_{i,jT}\right)}{1 + D_{i,2}} d\Phi(\nu^O) + ... + \int_{\Delta_{j-1}}^{\Delta_j} \frac{\exp\left(V_{i,jT}\right)}{1 + D_{i,j}} d\Phi(\nu^O), \quad (6)$$

and

$$s_{jO}(\beta_i) = \int_{\Delta_j}^{\Delta_{j+1}} \frac{\exp\left(V_{i,jO}\right)}{1 + D_{i,j+1}} d\Phi(\nu^O) + \int_{\Delta_{j+1}}^{\Delta_{j+2}} \frac{\exp\left(V_{i,jO}\right)}{1 + D_{i,j+2}} d\Phi(\nu^O) + ... + \int_{\Delta_J}^{\infty} \frac{\exp\left(V_{i,jO}\right)}{1 + D_{i,J+1}} d\Phi(\nu^O), \quad (7)$$

where $\Phi(\nu^O)$ denotes the standard normal distribution, $V_{i,jk} = V_{jk}\left(\beta_i, \nu^O\right)$, and the terms $D_{i,j} = D_j(\beta_i, \nu^O)$ are defined in the final column of Table 2.

[11] Because in our setting consumers choose among all possible alternatives, their consideration sets are "endogenous", i.e. a simplification of the choice set to the preferred channel of each product. This differs from a literature in industrial organization and marketing, where a consideration set typically refers to the subset of products that is actually available, due to bounded mental processing capabilities or limited information (e.g Sovinsky Goeree (2008). It is also distinct from a literature where the researcher does not observe the consumers' available choice set because of out-of-stocks, as in Conlon and Mortimer (2013) and Musalem et al. (2010).

To interpret this, consider the expression for $s_{jT}(\beta_i)$. The first term integrates consumers with a very low online valuation ($\nu_i^O \leq \Delta_1$), whose consideration set consists of the traditional channel for every product. The second term integrates over consumers with a higher online valuation ($\nu_i^O \in [\Delta_1, \Delta_2)$), who compare the online channel for product 1 with the traditional channel for all other products. The final term of $s_{jT}(\beta_i)$ integrates over consumers with the highest online valuations for whom the traditional channel may still be chosen ($\nu_i^O \in [\Delta_{j-1}, \Delta_j)$): these consumers compare the online channel for products $1, 2, ..., j-1$ with the traditional channel for products $j, ...J$.

The aggregate market share of product j at channel k is obtained by integrating (6) and (7) over β_i, so $s_{jk} = \int s_{jk}(\beta) dF_\beta(\beta)$. This adapted BLP model is appealing because of its substitution patterns between the traditional and online channel. To illustrate this, consider the cross-price effect of p_{jO} on s_{jT} (conditional on β_i). It can be verified that this is given by

$$\frac{\partial s_{jT}(\beta_i)}{\partial p_{jO}} = \frac{\alpha}{\sigma^O} \frac{\exp\left(V_{jT}(\beta_i, \Delta_j)\right)}{1 + D_j(\beta_i, \Delta_j)}. \tag{8}$$

Intuitively, substitution from the online to the traditional channel of product j stems from the mass of consumers who were close to indifferent between both channels of product j. Substitution between both channels will be strong when there is limited consumer heterogeneity in the valuation for the online channel (low σ^O).[12] In contrast, in a traditional BLP model, the cross-price effect of p_{jO} on s_{jT} is given by

$$\frac{\partial s_{jT}(\beta_i)}{\partial p_{jO}} = \alpha \int_{-\infty}^{\infty} \frac{\exp\left(V_{i,jT}(\beta_i, \nu^O)\right)}{1 + D(\nu^O, \beta_i)} \frac{\exp\left(V_{i,jO}(\beta_i, \nu^O)\right)}{1 + D(\nu^O, \beta_i)} dF_{\nu^O}(\nu^O), \tag{9}$$

where

$$D(\beta_i, \nu^O) \equiv \sum_{j' \in \mathcal{J}_k} \sum_{k' \in \{T,O\}} \exp\left(V_{j'k'}\left(\beta_i, \nu^O\right)\right).$$

This is the usual cross-price effect from a standard BLP model, which averages the substitution (conditional on β_i) over all online valuation types. Heterogeneity in the valuation for the online channel still plays a role, but it is mixed up with heterogeneity in the tastes for the product/channel alternatives $\varepsilon_{i,jk}$. Hence, even if there would be very limited heterogeneity in the valuation for online, there may still be weak substitution between both channels in the standard BLP model.

4.2 Specification, Estimation and Instruments

We first discuss the utility specification for the adapted BLP model. Next, we discuss how we calculate the market shares and invert the market share system to solve for the error term. Finally, we discuss the instruments used to estimate the model.

[12] As $\sigma^O \to 0$, the cross-price effect becomes arbitrarily large, and the diversion ratio (cross-price relative to own-price effect) approaches 1.

Specification We estimate the demand model based on panel data for products sold through both distribution channels across multiple countries and time periods. We reintroduce the subscript for country c (our 10 European countries), and also include a subscript for the period t (months during December 2012-March 2015).

Similar to the random coefficient for the online channel γ_i, we specify the random coefficients for a product characteristic n to be normally distributed, i.e. $\beta_i^n = \beta^n + \sigma^n \nu_i^n$ where $\nu_i^n \sim N(0,1)$. Furthermore, we decompose the unobserved product quality as perceived by a consumer in country c for product j at channel k into three parts $\xi_{c,jkt} = \xi_j + \xi_{c,k} + \widetilde{\xi}_{c,jkt}$. The utility of a consumer i located in country c for each alternative can then be written as:

$$u_{ic,jkt} = \delta_{c,jkt} + \mu_{i,jkt} + \varepsilon_{ic,jt},$$

where the mean utility part $\delta_{c,jkt}$ is

$$\delta_{c,jkt} = x_{jt}\beta - \alpha_c p_{jkct} + \xi_j + \xi_{c,k} + \widetilde{\xi}_{c,jkt}. \tag{10}$$

and the deviation from this mean is

$$\mu_{i,jkt} = \sum\nolimits_{n=1}^{N} \sigma^n \nu_i^n x_{jt}^n + \sigma^O \nu_i^O \times \mathbf{1}(k = O).$$

The product characteristics in the vector x_{jt} include CPU speed, the amount of RAM, weight, the display diagonal and the display resolution.[13] We let the mean price coefficient α_c vary across countries according to the earlier documented three fairly homogeneous income groups. We do not allow for heterogeneity in price sensitivity within these groups. As in Petrin (2002), we find that once we control for the different means between income levels, the estimated standard deviation of a random coefficient for price is statistically insignificantly different from zero. We allow for random coefficients for shopping online (through the parameter σ^O) and for two product characteristics (σ^n): the amount of RAM and the display resolution (pixels per inch).

We include a full set of product fixed effects ξ_j, which reflects systematic unobserved product quality common across countries (and time periods). We also include country and channel fixed effects $\xi_{c,k}$, reflecting unobserved valuations for portable PCs that are specific to each country and distribution channel. This flexibility thus also accounts for differences in the popularity of online shopping across countries. We also include month-of-year fixed effects and a general time trend to account for a gradual substitution out of portable PCs over time. Finally, we include country-specific trends for the online channel to account for evolving differences in the mean valuation of the online shopping channel across countries (stemming from changing demographics and/or improved quality of online websites). Any remaining unobserved quality is captured by the error term $\widetilde{\xi}_{c,jkt}$.

[13]The characteristics change over time, because we aggregate over products with different characteristics.

This includes omitted characteristics such as hard drive type or graphical processing chip, for which we assume consumers have a common valuation.

Estimation Estimating the adapted BLP model requires broadly similar steps as those for the standard BLP model, but the implementation is different. We start from the non-linear market share system for product j and channel k, sold at period t in country c:

$$s_{c,jkt} = \int s_{c,jkt}(\beta) dF_{\beta}(\beta), \tag{11}$$

where $s_{c,jkt}(\beta_i)$ is given by (6) and (7) after including a country subscript c and time subscript t. Market shares are sales relative to the potential number of consumers. We define the latter as proportional to total sales in the first period in each country, scaled up by a factor of two, which gives a comparable potential market across countries through the sample period.[14] We approximate the integral by simulating over the standard normal random variables ν_i. We then invert the market share system (market by market) to obtain a solution for the mean utilities $\delta_{c,jkt}(\mathbf{s}_{ct}, \sigma)$, where $\mathbf{s}_{ct}$ is the market share vector in country c and period t, and σ is a vector of the standard deviations of the random coefficients. Using (10), this gives

$$\widetilde{\xi}_{c,jkt} = \delta_{c,jkt}(\mathbf{s}_c, \sigma) - (x_{jt}\beta - \alpha_c p_{jkct} + \xi_j + \xi_{c,k}). \tag{12}$$

In the standard BLP model, this inversion exists and BLP suggest a contracting mapping. In our adapted BLP model, several complications arise. First, a solution does not necessarily exist and other methods than BLP's contraction mapping are required (see Berry and Pakes, 2007). Second, the market share integral is complicated by the fact that the consideration sets may change depending on the parameter values, implying discontinuities in the market share function.

As a solution to these problems, we approximate our adapted BLP model through a random coefficients nested logit model, where each product j is a nest with two alternatives: the traditional and online channel. The individual-specific taste parameter is then $\varepsilon_{ic,jt} + (1-\rho)\varepsilon_{ic,jkt}$ (Berry, 1994), where ρ is a nesting parameter measuring the extent of preference correlation for the two channels within the product nest. As $\rho \to 1$, we obtain the adapted BLP model. Online Appendix A.3 shows how the random coefficient nested logit model reduces to the adapted BLP model as $\rho \to 1$, and provides additional computational details. Note that our approach may be viewed as a "light version" of the scaling approach of Berry and Pakes (2007) to approximate the pure characteristics model: in our notation, they use $(1-\rho)\varepsilon_{ic,jkt}$ (without the $\varepsilon_{ic,jt}$ term) and let $\rho \to 1$. Unlike Song (2015) it enables the estimation of multiple random coefficients in a broad variety of settings.

[14] We obtain similar results for alternative scaling factors around two, or with a potential market as a fraction of population (20 percent).

Instruments A final step consists in constructing instrumental variables that satisfy the orthogonality conditions $E\left(\widetilde{\xi}_{c,jkt}|z_{c,jkt}\right) = 0$, so that they can be interacted with the model's predicted error (12) in a GMM estimator. We need a sufficient number of instruments to estimate both the mean valuations of the product characteristics (β), their standard deviations σ and the price coefficients α_c. We follow BLP and consider that the product characteristics other than price are exogenous, so that functions of the own and rival product characteristics can be used as instruments. There are two concerns with these characteristics-based instruments. First, similar to other markets for durable consumption goods, the market for portable PCs is characterized by product attributes that are improving over time. This may violate the assumption that the directly observable characteristics are fixed. Second, Armstrong (2016) shows that characteristics-based instruments can lose their identifying power when the number of products becomes large.

With regard to the first concern, our data is observed at a monthly frequency, which makes the assumption that characteristics can be treated as fixed for each individual market more reasonable. Apple, for example, updates its MacBook Pro on average every 301 days.[15] To alleviate these concerns further, we exclude CPU speed and the amount of RAM from the attributes that we use to compute our characteristics-based instruments. These two components of a laptop's design can be adjusted more easily and quickly than its weight, display diagonal and the display's resolution. The latter three attributes determine to a large extent the laptop's form factor and thereby also its overall design. Again, taking the example of Apple, the overall design of a laptop sees much fewer substantial changes over a period of several years than its internal components, such as the CPU, the amount of RAM or the size and type of the hard drive.

Second, with the results of Armstrong (2016) in mind and in the spirit of Gandhi and Houde (2019), we avoid summing over all available rival products in a market to compute our instruments. Instead, we partition the observed characteristics space to delineate groups of products that consumers are likely to perceive as relevant substitutes. Depending on where each laptop is located in this partition, we compute our instruments for this laptop by summing over the characteristics of rival products located in the same bin of characteristics space. As is standard, when forming these sums, we distinguish between observations that are sold by the same firm and observations that are sold by rival firms. Specifically, for each of the three remaining attributes in x_j (weight, diagonal and display resolution), we partition the marginal distribution into two segments: observations above and below the median. The partition of the characteristics space is then based on $2^3 = 8$ possible bins of each product's possible location in this characteristics space grid. For example, laptop j offering a less than median weight, display diagonal and display resolution has an address of $(0, 0, 0)$ in this space. We compute characteristics sums within and between firms, to obtain a total of six excluded instruments. We then interact these instruments with the three country group dummy variables (since we have a separate price coefficient per country group), so that we

[15] See the Buyer's Guide on `https://buyersguide.macrumors.com/#Mac`.

have eighteen excluded instruments in total.[16] Furthermore, we also constructed a product-specific cost shifter, by interacting an input price (freight costs) with product characteristics (weight and resolution).[17]

Table A.2 of online Appendix A.2 presents the results of first-stage regressions of price on the instruments. F-statistics for the set of excluded instruments are very high, even after adding fixed effects. So we can comfortably reject the null hypothesis that the characteristics space instruments are not relevant.

4.3 Empirical Results

We first discuss the demand parameter estimates and then the resulting price elasticities.

Parameter Estimates Table 4 shows the main parameter estimates of the adapted logit and two specifications of the adapted BLP model.[18] The common parameters (i.e. the mean valuations) are broadly comparable across models, though the substitution patterns may differ drastically as we discuss further below. The first random coefficients specification, BLP(I), contains the standard deviations of the valuations of three characteristics: the online channel, RAM and display resolution. We calculate a Wald test for the hypothesis that all estimated standard deviations of the random coefficients are statistically insignificant, $H_0 : (\widehat{\sigma}_{on}, \widehat{\sigma}_{ram}, \widehat{\sigma}_{ppi}) = \mathbf{0}$. The Wald statistic of 45.60 shows that the null can be rejected at the 99 percent confidence level. The second specification, BLP(II), includes two additional random coefficients, one for price (interacted with income draw) and one for CPU speed. Both coefficients are statistically insignificant and appear difficult to identify, and the Wald test is virtually the same as in BLP(I).[19] We therefore focus on BLP(I) in our subsequent discussion and analysis.

The mean price coefficients have the expected sign and are precisely estimated. Moreover, the consumers' price sensitivity is highest in the low income country group, and lowest in the high income country group, an intuitive finding that also applies to the other specifications.[20]

[16]We considered implementing efficient or "optimal" instruments, as discussed in Reynaert and Verboven (2014) and Conlon and Gortmaker (2020). However, these are more tedious to compute in our approximation to the adapted BLP model, and since we obtain relatively precise estimates for the random coefficients we did not pursue this further.

[17]This follows Reynaert and Verboven (2014), but it does not affect the estimates by much in our setting.

[18]Online Appendix A.2 provides complete results and a comparison with the standard logit and BLP models. It also presents estimates for a more disaggregate product definition based on model names; and estimates where we aggregate to the quarterly level. We obtain comparable findings but find the more aggregate product definition more appealing because it combines very similar model names of short time span or limited country coverage.

[19]Since we cannot reliably identify within-country heterogeneity in price sensitivity, we caution that we can investigate distributional effects only between and not within countries.

[20]In Table A.6 of online Appendix A.2, we assess the role of our instruments. First, we estimated the logit model using ordinary least squares, i.e. without instruments. As expected, this results in a substantial underestimation of the price coefficients. The OLS estimates are between 4 and 9 times smaller than the IV estimates; they imply inelastic demands for almost 84 percent of all observations, while with instruments all observations are price elastic. Second, we include additional cost shifters as instruments in both the logit and BLP models. In line with the importance of shipping costs highlighted by e.g. Carriere-Swallow et al. (2022), we use airfreight rates from Asia to

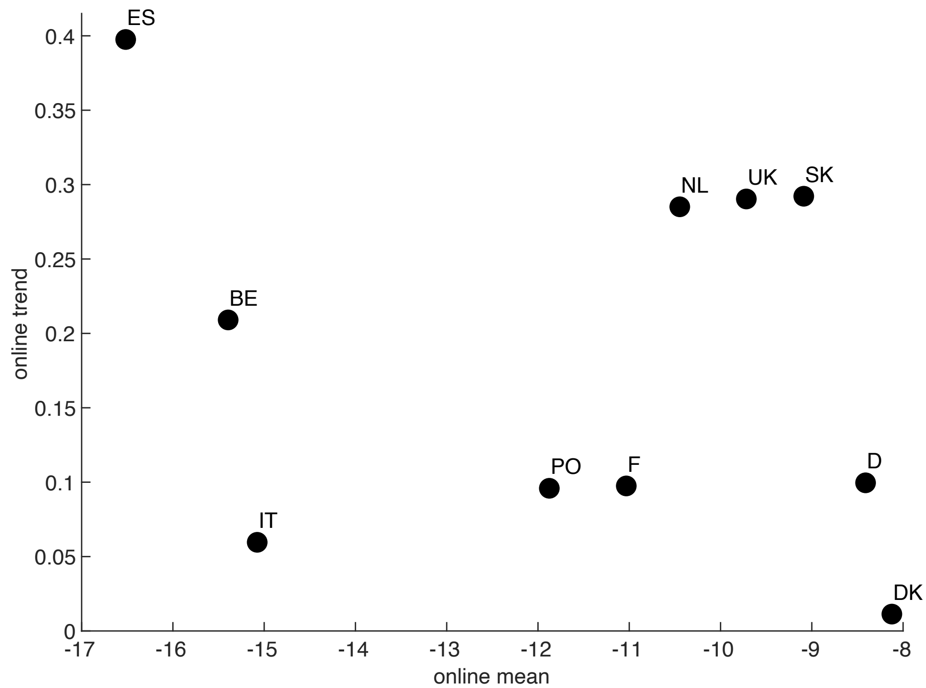
Table 4: Demand Estimates - Price and Characteristics

	Adapted Logit	Adapted BLP (I)		Adapted BLP (II)	
		mean	std. dev.	mean	std. dev.
α_L	**.0072**	**.0069**		**.0068**	
	(.0008)	(.0014)		(.0077)	
α_M	**.0064**	**.0059**		**.0059**	
	(.0008)	(.0013)		(.0217)	
α_H	**.0048**	**.0044**		**.0045**	
	(.0007)	(.0012)		(.0304)	
Income interaction					**-.0009**
					(.1326)
Online			**8.982**		**9.205**
			(2.507)		(5.308)
CPU Speed	**.6091**	**.8608**		**.8362**	**.0280**
	(.1290)	(.2005)		(.4027)	(12.45)
RAM	**.0534**	**-.2134**	**.2431**	**-.1917**	**.2277**
	(.0093)	(.1280)	(.0810)	(.1431)	(.0776)
Weight	**-.1440**	**-.3094**		**-.3155**	
	(.1527)	(.1927)		(.2607)	
Diagonal	**.1329**	**.1598**		**.1579**	
	(.0239)	(.0338)		(.0381)	
Resolution	**1.138**	**1.294**	**.0973**	**1.255**	**.1341**
	(.2672)	(.7398)	(7.881)	(.8557)	(9.793)
Constant	**-7.854**	**-8.417**		**-8.440**	
	(.8752)	(1.360)		(1.415)	
Trend	**-.0777**	**-.0869**		**-.0867**	
	(.0075)	(.0127)		(.0504)	
Wald Stat.	-	45.60		45.79	
Crit. Value		11.34		11.34	
$\overline{\eta}_{jj}$	-3.89	-3.98		-3.87	
$\#\ \eta_{jj} > -1$	0	0		0	
$\overline{\eta}_{jT,jO}$	110.0	.0956		.0890	
$\overline{\eta}_{jO,jT}$	265.1	.2741		.2627	
$\overline{D}_{jT,jO}$	.9472	.0247		.0239	
$\overline{D}_{jO,jT}$	.9847	.0688		.0672	

Note: Based on 10 288 observations. Standard errors are shown in parentheses. Product fixed effects and channel-country fixed effects and trends are included. The critical value for the Wald statistic refers to a 99 percent significance level and three degrees of freedom. 1 000 modified latin hypercube sampling (MLHS) draws and 30 different starting values for the nonlinearly entering coefficients were used during the estimation. The adapted demand models are estimated with the approximations discussed in section 4.2 and online Appendix 4.3, with $\rho = 0.99$ for the adapted logit and $\rho = 0.9$ for the adapted BLP. The price coefficients vary between three country groups that are color coded in Figure A.1. $\overline{\eta}_{jj}$ is the average own price elasticity of product j (from a joint price increase of both the traditional and online variant). $\overline{\eta}_{jT,jO}$ and $\overline{\eta}_{jO,jT}$ are the average cross-price elasticity between the traditional and online channel of the same product (over products available at both channels). $\overline{D}_{jT,jO}$ and $\overline{D}_{jO,jT}$ are the corresponding diversion ratios.

Europe interacted with diagonal, weight and the product of diagonal and weight. This gives very similar parameter estimates as our model with only BLP instruments.

Figure 3: Estimated Online Means and Trends



Note: Based on 10 228 sample observations and Adapted BLP(I), reported in Table 4 and Table A.3-A.4.

As expected, consumers have a higher mean valuation for machines with a faster CPU, a larger display size (diagonal) and a larger display resolution. Furthermore, consumers have a lower though not precisely estimated mean valuation for portables with a higher weight and RAM. The standard deviation for the RAM valuation is large and significant, showing there is a lot of unobserved consumer heterogeneity for this attribute. We also include a trend to capture general changes in the demand for portable PCs, and estimate this trend to be negative and highly significant, showing the value for the outside option is increasing over time. One interpretation is the introduction of smartphones and tablets (as falling sales for portable PCs during our sample period correspond to growing demand for smartphones and tablets). Another interpretation is that portable PCs are becoming better (more durable) over time (as suggested by Eizenberg, 2014).

Finally consider the consumers' valuations for the online distribution channel. Figure 3 summarizes the country-specific mean valuations, and trends in these mean valuations for our preferred adapted BLP (I) specification. As evident from the horizontal axis of Figure 3, all countries have negative mean valuations for the online channel and there are considerable differences across countries, consistent with the online shares reported in Table 1. Furthermore, countries with the highest positive trends (vertical axis of Figure 3) often showed the strongest online share increases in Table 1. Finally, Figure 3 suggests there is some negative correlation between the country intercepts and trends, indicating that the late coming countries are catching up. We will consider the implications of this in our counterfactual analysis of online market integration.

Although the country-specific mean valuations for the online channel are negative, the standard deviation of the online valuation is precisely estimated and relatively large, suggesting sizeable consumer heterogeneity. This shows that there is substantial within-country heterogeneity in the valuation of the online distribution channel, with considerable fractions of consumers who like the online channel in each country. As we discuss below, this heterogeneity has implications for the cross-price elasticities and diversion ratios between the traditional and online channel.

In sum, our adapted BLP model yields intuitive results consistent with the preliminary evidence reported in section 2. The price sensitivity differs across countries according to their income levels. Consumers show a significant valuation for several product characteristics. There is also important consumer heterogeneity, in particular regarding the valuation of the online distribution channel. Part of this heterogeneity refers to cross-country differences that line up with our earlier evidence on online market shares. But there is also significant unobserved heterogeneity within a country.

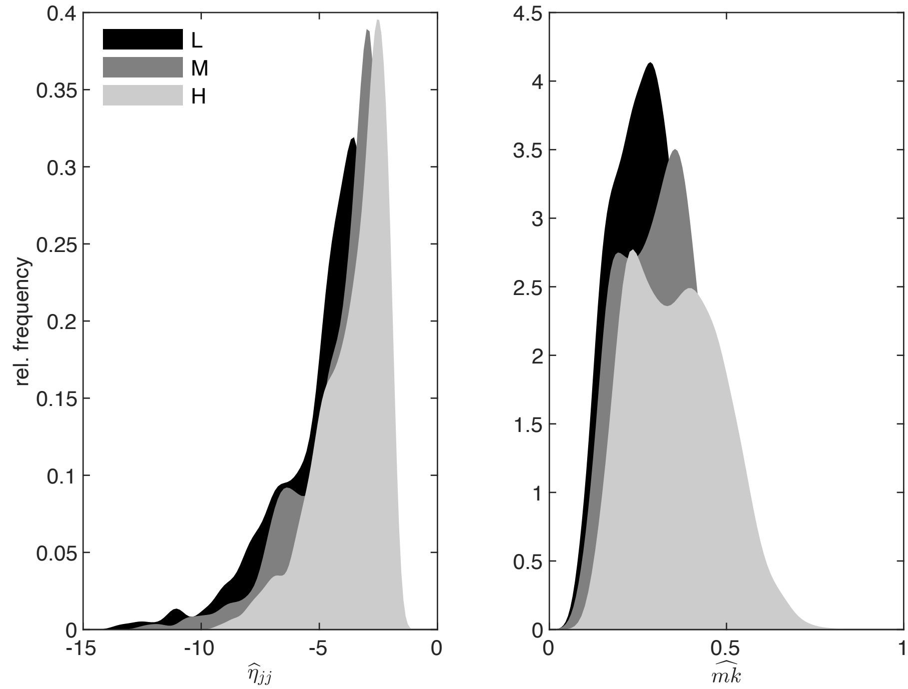
Price Elasticities and Diversion Ratios Table 4 also shows the average own-price elasticities of demand over all observations for the different demand models. These averages are fairly similar, varying between -3.98 and -3.87. The left panel of Figure 4 shows the entire distribution of the own-price elasticities, conditional on the three country income groups for the first BLP specification. Price elasticities are on average higher for the low income group, and lower for the medium and especially the high income group (as reflected in a shift to the right of the elasticity distribution for these groups).

While the own-price elasticities in Table 4 are similar across the demand models, this is not the case for the cross-price elasticities and diversion ratios. The most interesting differences relate to substitution between the two distribution channels. We calculate the cross-price elasticities and diversion ratios between the traditional and online variant for every product, i.e. $(\eta_{jO,jT}, \eta_{jT,jO})$ and $(D_{jO,jT}, D_{jT,jO})$ for every product j, and we average this over products.[21] The final rows of Table 4 show the results from this comparison. The adapted logit model generates extremely high product-level cross-price elasticities between both channels, and an average diversion ratio close to one. This is because the individual taste shock is specific only to the product and not to the distribution channel ($\varepsilon_{i,j}$), and there is no other heterogeneity in the valuation of the online channel.[22] As a result, the two channels of the same product are by construction essentially perfect substitutes, implying very high cross-price elasticities.

[21] The underlying demand derivatives are given by (8) and (9) for the adapted and standard BLP, respectively.

[22] The average cross-elasticity is still finite and the diversion ratio not exactly equal to one, because we approximate the model with $\rho = 0.99$. Note also that the standard logit ($\rho = 0$) generates extremely low cross-price elasticities between both channels. This is due to the artificial individual taste shock included for every product and channel combination ($\varepsilon_{i,jk}$).

Figure 4: Distribution of Own-Price Elasticities and Markups



Note: Based on Adapted BLP (I), reported in Table 4 and Table A.3-A.4. The average markups in the low-, medium- and high-income country groups are 26.1, 29.8 and 36.1 percent, respectively.

In contrast, in the adapted BLP model we found that there is considerable heterogeneity in the valuation for the online channel (σ^O). This implies much lower and more plausible cross-channel substitution, as measured by the cross-price elasticities or diversion ratios. It is important to stress that the extent of cross-channel substitution in the adapted BLP model is mainly driven by the obtained estimate of the standard deviation for the valuation of the online channel (σ^O). If we would have obtained a lower estimate of σ^O, then the cross-elasticities and diversion ratios would have been even higher, and vice versa (as can also be seen from the cross-demand derivative (8) and from the extreme case of $\sigma^O = 0$ in the previously discussed adapted logit).

4.4 Oligopoly and Markups

To compute markups and back out marginal costs, we use a standard oligopoly model of multi-product price-setting firms, similar to for example Sovinsky Goeree (2008), Eizenberg (2014) and Song (2015) for the PC industry. This approach can be justified under a competitive retail sector, or more generally under an imperfectly competitive retail sector with efficient contracting between producers and retailers (no double marginalization effects). Rey and Vergé (2010, 2019) have a model of "interlocking relationships" between producers and retailers that yields this outcome.

Rey and Vergé (2019) obtain this outcome under general conditions when contracts are secret. As such, the markups may be interpreted as the combined markups of the producers and retailers. Similarly, the marginal costs can be interpreted as the sum of the producers' marginal costs (all Asian manufacturers) and the retailers' local distribution costs, which may vary across countries. We do not attempt to explicitly model possibly more complicated relationships between producers and retailers, because we observe only retail prices and not wholesale prices, and only the total sales per product, and not the sales broken down by retailer (as in e.g. Bonnet and Dubois (2010)).

More specifically, let mc_{jkct} be the (constant) marginal cost of product j at distribution channel k in country c and period t and let $\mathcal{F}_{fk}$ be the set of products sold by firm f at channel k. The profits of firm f in country c are the sum of the profits over all its products sold through both distribution channels:

$$\pi_{cft} = \sum_{j' \in \mathcal{F}_{fk't}} \sum_{k' \in \{T,O\}} \left(p_{j'k'ct} - mc_{j'k'ct}\right) s_{c,j'k't} L_{ct}. \tag{13}$$

The market share $s_{c,jkt}$ in (13) is given by (11). Because markets are nationally segmented, this depends only on the prices of alternatives in the same country.

Firms are multi-product Bertrand price-setting firms. They choose the prices of their products to maximize profits, taking as given the prices of the other firms. For each market c and period t, this gives a system of first-order conditions for the optimal prices of every product j and channel k. Let $q_{c,jkt} = s_{c,jkt} L_{ct}$ and let $\mathbf{p}_{ct}$, $\mathbf{q}_{ct}$ and $\mathbf{mc}_{ct}$ be vectors with elements $p_{c,jkt}$, $q_{c,jkt}$ and $mc_{c,jkt}$. Furthermore, let $\mathbf{\Omega_{ct}}$ be a matrix for country c in period t with own- and cross-demand derivatives $\Omega_{jkct,j'k'ct} = \partial s_{c,jkt} / \partial p_{j'k'ct}$, and define the ownership or holding matrix $\mathbf{H_{ct}}$ with entries $H_{jkct,j'kct} = 1$ if $j, j' \in \mathcal{F}_{fkt}$ and zero otherwise. We can then write the system of first-order conditions in matrix notation, to calculate the marginal cost vector in country c and period t as the difference between the price and equilibrium markup:

$$\widehat{\mathbf{mc}_{ct}} = \mathbf{p}_{ct} + \left[\mathcal{H}_{ct} \odot \Omega_{ct}\right]^{-1} \mathbf{q}_{ct}. \tag{14}$$

The implied percentage markups for product j at channel k are defined as $(p_{jkct} - \widehat{mc}_{jkct})/p_{jkct}$.

The right panel of Figure 4 plots the markup distributions by median income groups. Country groups with higher median per-capita incomes have markups with distributions that are shifted to the right. The average markups in the low-, medium- and high-income country groups are 26 percent, 29 percent, and 35 percent, respectively. The average markup levels fall somewhere in the middle of other studies for the US PC market: lower markup estimates by Sovinsky Goeree (2008) and Eizenberg (2014) and higher estimates by Song (2015). The markups are also in line with accounting information, with annual gross margins of 37 percent and Ebitda margins of 23 percent in 2019 according to CSI market.

To have an idea on the extent to which local distribution costs differ across countries, we regress marginal cost on the vector of product attributes x_{jt} (including a time trend), product fixed effects ω_j and a set of fixed effects ω_{kc} to account for systematic differences in local costs between countries c and distribution channels k:

$$\widehat{mc}_{jkct} = x_{jt}\gamma + \omega_j + \omega_{kc} + \widetilde{\omega}_{jkct}. \tag{15}$$

Table A.5 in online Appendix A.2 reports the results. CPU speed, RAM, display diagonal and display resolution have a positive effect on marginal costs, whereas weight has a negative impact. Local marginal costs show variation across countries. Belgium and Denmark are estimated to be the high-cost countries in both the traditional and online channels, while France, Germany and the UK are estimated to have the lowest marginal costs in both channels on average. Although differences in marginal costs between countries are not unusual because of differing distribution costs, we caution that the estimates are based on our assumption of Bertrand price-setting behavior. For the counterfactuals that we discuss below, we constrain the product-level marginal costs to be equal between countries in the online distribution channel, because all laptops are actually produced in Asia. Our findings are robust to allowing for country-specific online channel marginal cost shifters, however.

5 The Impact of Reducing Cross-Border Trade Restrictions

Our goal is to assess the impact of removing cross-border trade restrictions in online markets, following the ban of geo-blocking practices. This event essentially increases the consumers' online choice set to all countries (possibly at the expense of extra shipping costs). This, in turn, leads to a new integrated market equilibrium: online prices may adjust and converge across countries, with possible indirect price effects on the traditional channel. Although we would ideally perform our analysis on all EU countries, our analysis is already quite comprehensive because the ten included countries cover 84 percent of GDP in the EU in 2015.

To assess the effects, we make use of the demand estimates and the backed out marginal costs from the pre-ban situation with nationally segmented markets, as analyzed in section 4. Subsection 5.1 provides an overview on how we model the post-ban online market integration equilibrium, with formal details in online Appendix A.4. Subsection 5.2 then reviews the main results from these counterfactuals, while subsection 5.3 provides a discussion with several extensions .

5.1 Post-integration market equilibrium

We first discuss our basic approach to model the post-integration market equilibrium, and then discuss caveats and extensions.

Post-integration Product Availability and Equilibrium With nationally segmented markets, consumers can buy products only in their own country. The market shares thus depend only on the utilities for the alternatives available in the consumers' own country, and prices are set according to local demand and cost conditions. With integrated markets, consumers in country c essentially face an increased choice set because they can now also buy in other countries d. We continue to rely on our adapted BLP model, which limits the dimensionality of the individual taste parameter to the products j. Hence, we do not only eliminate artificial differentiation between the same products sold through a different channel (as in our empirical analysis pre-integration), but we also eliminate artificial differentiation between the same products sold in different countries (post-integration). Prices for the same online product are then equalized across countries, so that firms choose a single online price per product.

To understand the economic effects of opening up borders in online markets, we consider two scenarios of product availability.

> *Pre-integration availability (PIA):* In this scenario, consumers only obtain access to the products in other countries that were already available in their own country. This scenario is helpful to understand the price convergence effect of market integration, because it reduces the possibility to engage in cross-country price discrimination without changing the consumers' available product choice sets.
>
> *Full availability (FA):* In this scenario, consumers can also obtain access abroad to other products that were previously not available in their own country. This scenario combines the effects from removing price discrimination and obtaining more choice.

Formally, the difference between the two scenarios comes from how we construct the choice sets in the demand equation. Before integration, a consumer from country c has a choice set for online products $\mathcal{J}_{Oc}$. Under integration with FA, consumers have the choice sets $\mathcal{J}_{Od}$ for all countries $d \in C$. Under integration with PIA, a consumer in country c has more limited choice sets $\mathcal{J}_{c,Od} = \mathcal{J}_{Oc} \cap \mathcal{J}_{Od}$ for all countries $d \in C$ (where $\mathcal{J}_{c,Oc} = \mathcal{J}_{Oc}$ is the local choice set already available before integration). Under both scenarios, we then compute the new market equilibrium and the implied welfare changes.

Caveats and Extensions We caution that these two scenarios provide a simplification of possible post-integration equilibrium outcomes. In practice, the geoblocking ban may also induce other changes. First, firms may endogenously adapt their product portfolios. For example, they may decide to no longer offer certain products that were supplied to low income countries before integration. Accounting for such product portfolio effects in response to market integration would require to explicitly model the product decisions, as done for example by Chaves (2020) in response to a tax policy on car engines. Second, firms may also respond to market integration in other ways, for example by coordinating their advertising decisions or by abandoning country-specific sales during national holidays and instead offer European-wide sales.

We do not model these possible additional effects, but we instead consider two other extensions to our basic approach. First, we compute counterfactuals in future years, to account for the fact that online purchases showed a positive trend in most countries. Second, we compute counterfactual equilibria that account for the presence of shipping costs between countries.[23] This may be interpreted as a move to partial integration as opposed to full integration in the absence of shipping costs.

5.2 Results

We perform our counterfactuals based on the first specification of the adapted BLP model (BLP (I) in Table 4), and focus here on the case of no shipping costs. We compute the counterfactual equilibria (including the predicted status quo) for each month in our sample. We include the product-specific ξ_j, channel/country-specific $\xi_{c,k}$ as well as time effects in the mean utility term, and similarly include ω_j and ω_{kc} and time effects in the marginal cost term. For simplicity, we set the residual unobserved quality and marginal cost error terms $\widetilde{\xi}_{c,jkt}$ and $\widetilde{\omega}_{jkct}$ to their expectation, i.e. zero.[24] We then arrive at a weighted annual average across periods by using the pre-ban total number of units sold at each month as weights.

As discussed, we consider two scenarios to evaluate the impact of reducing cross-border trade restrictions after a geo-blocking ban. Under pre-integration availability (PIA), consumers have online foreign access to only those products that they could previously already purchase at home. Under full availability (FA), consumers can buy all products online abroad, even those that were not previously available in their own country.

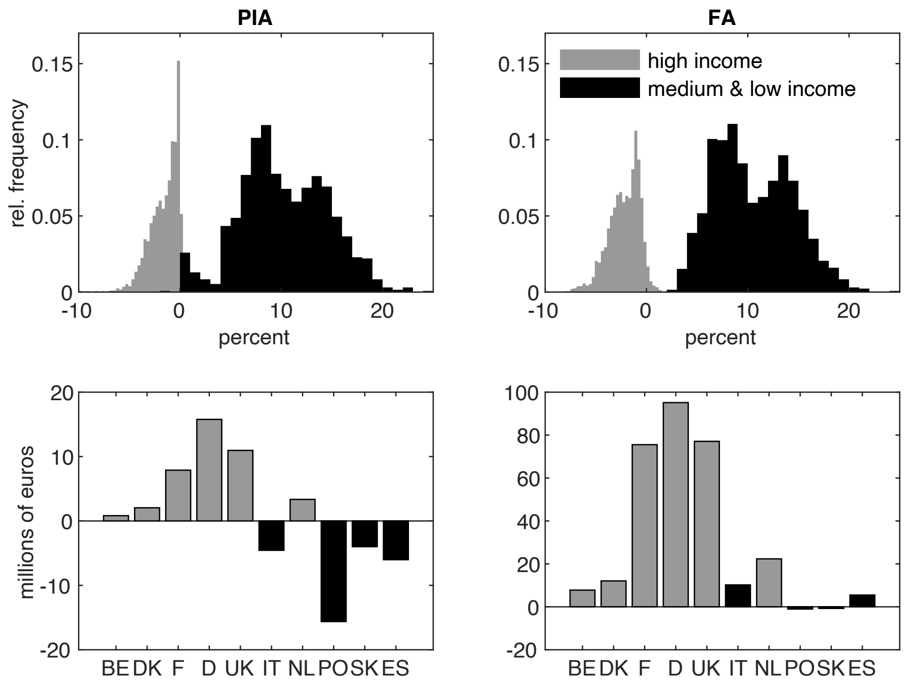
We first discuss the distributional effects on consumers across the different countries, and then consider the total effects across all EU countries.

Distribution of Consumer Gains across Countries Figure 5 summarizes our main findings on how a geo-blocking ban may have different effects across countries. The two top graphs show the distribution of percentage price changes in the online channel after a geo-blocking ban, separately for the high income countries (blue) and the medium and low income countries (red). Under both scenarios, almost all products become less expensive online in the high income countries, and

[23]The European Commission distinguishes between justified and unjustified geoblocking practices. While access to online channels in other countries must not be blocked, it may be justified to charge foreign consumers additional fees for the shipping costs involved in serving them.

[24]Explicitly incorporating them in cross-border counterfactuals would require an assumption on their interpretation. For example, the unobserved demand residual may reflect a combination of a temporary local taste shock (and hence apply to foreign purchases by local consumers) or quality shock (and hence apply to domestic purchases by foreign consumers).

Figure 5: Counterfactual Online Price Changes and Consumer Surplus Changes



Note: Based on Adapted BLP(I), reported in Table 4 and Table A.3-A.4. PIA and FA refer to the scenarios of Pre-Integration Availability and Full Availability. The group of high-income countries are Belgium, Denmark, France, Germany, the UK and the Netherlands, while the low- and middle-income countries are Italy, Spain, Poland and Slovakia. Price changes relative to the segmented markets benchmark equilibria are measured in percent. Thus, the number 10 corresponds to an increase of post-ban prices of ten percent.

almost all products become more expensive online in the medium and low income countries.[25] This is consistent with our earlier finding that consumers from the high income countries are less price sensitive, which was reflected in higher markups and prices in these countries. If consumers only obtain foreign access for products they could previously purchase at home (PIA scenario, top left), the average online price decrease is 1.5 percent in the high-income countries, while the average online price increase is 7.9 percent in the medium income countries and more than 12 percent in the low-income countries. If consumers obtain full access to all products abroad (FA scenario, top right), the average effects are slightly larger. Online prices drop by 2.2 percent in high income countries, while they increase by 7.6 and 12.8 percent in the medium-income and low-income countries, respectively.[26] As such, these findings show how banning geo-blocking and thereby achieving

[25]The pattern is similar in the traditional channel, but much less pronounced because of limited substitution between both channels (see Figure A.2 in online Appendix A.2).

[26]We also computed sales-weighted averages of the product characteristics after the geo-blocking ban. Under PIA these averages change only very slightly (by less than 0.2 percent). Under FA they drop by between 1 and 2 percent, consistent with our earlier reported finding (Table 2) that products becoming available after the geo-blocking ban tend to have slightly lower characteristics.

online market integration is equivalent to banning third-degree price discrimination between more and less price sensitive consumers. In this case, this actually implies a transfer from the low and medium to the higher income countries.

It is interesting to compare this finding to Dubois, Gandhi and Wasserman (2019). As discussed in the introduction, in their setting (pharmaceuticals) price convergence between countries obtains because of price regulations, whereas in our setting it occurs because of cross-border trade opportunities. But some of their conclusions show interesting parallels. They find that price constraints between the US and Canada would reduce US prices only slightly, and instead mainly raise prices in the smaller country Canada. Hence, both direct price constraints or indirect constraints through cross-border trade may result in comparable price convergence effects. But other implications such as consumer welfare effects may differ, and we turn to this next.

While a look at price changes is intuitive, it does not give a complete picture of the distribution of consumer gains across countries. The two bottom graphs of Figure 5 show the impact on consumer surplus in the different countries. If the ban opens foreign access only to products that were already available at home (PIA scenario, bottom left), consumers in the high income countries gain at the expense of consumers in the low and medium income countries. For example, consumers in Germany and the UK gain by respectively 15.6 and 11.0 million Euro, whereas consumers in Poland and Spain lose by 15.5 and 6.3 million Euro. In contrast, if the ban opens foreign access to all consumers (FA scenario, bottom right), the low and medium income countries also gain (or lose only slightly, though the gains are again much higher for the high income countries, for example 93.6 and 77.2 million Euro in Germany and the UK. Intuitively, the PIA scenario mainly involves a transfer of benefits because it purely captures the price convergence effect, while the FA scenario implies gains to all countries because it also captures the product choice expansion effect.

Table 5 takes a further look at the country effects. In addition to consumer surplus changes, it also shows price and output changes broken down by the two distribution channels. This shows the extent to which there are spillover effects to the traditional channel. The top panel (pre-integration access) gives the sharpest conclusions (because it abstracts from the product choice expansion effect). Countries with high consumer surplus gains (in per capita terms), also see the highest online price drops. Furthermore, they experience some modest price drops in the traditional channel. For example, in Denmark online prices drop by 1.73 percent, inducing a price drop on the traditional channel by 0.05 percent. The extent of substitution is lower in Belgium, because the online channel is less important there. Similarly, in countries with online price decreases there are also increases in online sales (e.g. +1 percent in Denmark), while traditional sales drop because the price drops on the traditional channel are too modest. The reverse findings hold for countries with consumer surplus losses (i.e. price increases online, modest price increases offline, and drops in online sales with a modest shift to traditional sales).

The bottom panel of Table 5 (full access) gives broadly comparable conclusions regarding the

Table 5: Counterfactual Outcomes: Effects by Country

	Pre-Integration Access (PIA)				
		Δp (%)		ΔQ (%)	
	ΔCS (mln euros)	traditional	online	traditional	online
BE	0.878	-.023	-2.66	-.067	1.83
DK	2.055	-.061	-2.08	-.130	.989
F	8.197	-.035	-2.00	-.068	1.10
D	15.67	-.045	-1.48	-.081	.704
UK	10.95	-.062	-1.89	-.112	.910
IT	-4.533	.060	7.78	.175	-6.05
NL	3.330	-.049	-1.86	-.095	.890
PO	-15.47	.182	14.0	.532	-8.79
SK	-3.995	.417	14.3	1.12	-8.29
ES	-6.299	.088	8.87	.227	-6.24
All	10.78	-.001	-.131	.028	-.158
	Full Access (FA)				
		Δp (%)		ΔQ (%)	
	ΔCS (mln euros)	traditional	online	traditional	online
BE	7.644	-.030	-3.15	-.857	17.2
DK	12.05	-.081	-2.71	-1.09	6.02
F	73.70	-.043	-2.57	-.984	10.4
D	93.58	-.064	-2.11	-.689	4.34
UK	77.24	-.087	-2.52	-1.07	6.68
IT	9.430	.072	7.32	-.585	13.1
NL	22.04	-.070	-2.55	-.887	6.21
PO	-1.471	.201	14.0	-.276	.594
SK	-0.786	.429	14.2	-.101	-1.33
ES	4.826	.092	8.36	-.411	5.74
All	298.2	-.010	-.707	-.752	6.05

Note: Based on Adapted BLP (I), reported in Table 4 and Table A.3-A.4. Output changes are computed for the ten populations of consumers, while price changes are computed for the products available for sale in each of the ten countries. For price changes, we use units sold in the benchmark segmented markets equilibria as weights. For relative quantity changes, we use all 13 dates to arrive at the numbers.

percentage price and output changes: countries with the highest consumer surplus gains show the highest drops in online prices, traditional prices only slightly increase, and there is a shift from traditional to online sales. And the reverse is true for countries with the lowest consumer surplus gains.

Total effects We now discuss the total effects across the EU from integrating online markets through the geo-blocking ban. Table 6 shows the results. To put the predicted annual consumer and producer surplus changes (in million euro) in perspective, note that the actual annual revenues in the EU amount to 1042 million euro for the traditional channel and 283 million for the online channel.

Table 6: Counterfactual Outcomes: Total Effects across Countries

	Pre-Integration Access (PIA)	Full Access (FA)
ΔCS	10.8	298.2
$\Delta \Pi$	-10.9	8.46
ΔQ (%)	-.02	.97
ΔQ_{trad} (%)	.03	-.75
ΔQ_{on} (%)	-.16	6.02

Note: Based on Adapted BLP (I), reported in Table 4 and Table A.3-A.4. Changes in consumer surplus and changes in profits are measured in millions of euros per year. These may be compared with actual annual revenues in the EU of 1042 million euro for the traditional channel and 283 million euro for the online channel.

We find that integrating online markets results in small total EU effects if consumers do not have the possibility to purchase new products after the ban (PIA scenario). Total output and average EU prices remain essentially unchanged, with a small shift out of online (-0.2 percent) into the traditional channel. Consumer surplus increases by 11 million annually (or slightly less than 1 percent of annual revenues. But producer surplus drops by a similarly small amount, so that the total welfare effect is negligible. The reason for the small total welfare effects is that this scenario purely captures the price convergence effect. This strongly shifts benefits between countries (as we saw before), but does not have important effects at the EU level.

In contrast, integrating online markets implies more sizeable total EU effects if consumers can purchase products that were not available in their own country (FA scenario). Total output increases by about 1 percent, and this implies a sizeable increase in online sales (by 6.0 percent). Consumer surplus now increases by 298 million euros. The larger consumer benefits in this scenario are of course due to the product choice expansion effect after the ban on geo-blocking, which is much higher than the impact from the pure price convergence effect. The geo-blocking ban has a small positive effect on firm profits, implying the overall welfare impact is close to the consumer surplus impact.

The small positive profit effects under full access raises the question why firms did not voluntarily allow access before if they seem to be essentially indifferent. One interpretation is that there are unmodelled efficiency reasons for geo-blocking, for example free-riding issues in the provision of sales and after-sales services (e.g. Telser, 1960; Klein and Murphy, 1988), and difficulties with providing these services to customers from abroad.

5.3 Discussion

In sum, integrating online markets has large distributional effects between countries. The total EU effects on consumers and welfare may also be sizeable, but mainly because of increased product choice expansion rather than because of a price convergence effect as often implicitly assumed to be relevant in policy circles. To further understand the impact of the geo-blocking ban, it is instructive to consider how our estimates change under various alternative assumptions.

Standard BLP First, we based our counterfactuals on the adapted BLP model, with an idiosyncratic taste parameter at the level of the product ($\varepsilon_{ic,j}$) instead of the product, channel and country-of-purchase ($\varepsilon_{ic,jkd}$). This is important in our setting, not only for uncovering reasonable substitution patterns between the traditional and the online channel, but also for adequately measuring the welfare effects without including artificial gains from making the same products available in other distribution channels or countries.

To appreciate this, we reconsidered our counterfactuals of Table 6 based on a standard BLP model, and show this in Table A.9 of online Appendix A.2. In both scenarios, this demand model predicts a very large increase of total output (by between 3.6 and 4.4 percent) and of output in the online channel (by about 50 percent). Intuitively, the standard BLP model implies a strong outward shift in demand because the same products mechanically create new variety at different channels and countries. Similarly, in both scenarios the consumer surplus increase from the ban would be greatly overestimated. Consumer surplus gains would exceed 2.5 billion euros annually, or roughly 10 times larger than the estimated gains in our adapted BLP model (FA scenario). Finally, the standard BLP model would imply a large positive producer surplus increase by more than 400 million euro, or more than 30 percent of annual revenues. This follows again from the mechanically created additional product variety. But this is at odds with a simple revealed preference argument that the firms themselves prefer to restrict cross-border trade through geo-blocking practices. Relating to our earlier discussion, the standard BLP model could rationalize this only under very large efficiency gains in the provision of services.

Increasing online channel Second, we performed our counterfactuals as averages across months within our sample (January 2012 to March 2015). However, during this period the level of e-commerce was still relatively limited (not larger than 20 percent in most countries). The benefits may further increase over time, as e-commerce will become more important, also in many other consumer electronics sectors. This possibility was also suggested by our estimated positive trends for the valuation of the online channel, especially in countries with relatively low online sales at the start of our sample.

To account for the increasing importance of the online channel, we recompute the predicted total effects of online integration (based on in-sample predictions in Table 6, by assuming the trends continue for one and two more years. As shown in Figure A.3 of online Appendix A.2, online market integration would imply even stronger redistribution from low to high income countries after two years. Furthermore, the total EU effects become stronger after two years (Table A.10). For example, under full availability (FA) online integration would raise total output by 2 percent after two years (compared with 1 percent within sample), and raise consumer surplus by 340 million Euro after two years (compared with 300 million within sample). These findings show that online market integration has important increasing effects over time, which would be further reinforced after the recent surge in online shopping during the COVID-19 pandemic.

Shipping costs Third, our counterfactuals above assumed there are no shipping costs, implying full market integration after the geo-blocking ban. In practice, there may be remaining trade costs because of physical shipping costs, or additional frictions relating to different default specifications (including keyboards), linguistic barriers (including different standard keyboards), delivery time, warranties, etc.

To consider the role of such frictions, we incorporate different values of shipping costs borne by consumers when purchasing abroad. We start from physical shipping costs, and then extend this to higher levels, possibly differing between neighboring and non-neighboring countries.[27] We focus on the consumer surplus effects in the pre-market availability scenario (PIA), and report this in Table 7 (see also Figure A.4 and Figure A.5 of online Appendix A.2). Our findings remain broadly comparable: prices drop and consumer surplus increases in high income countries, at the expense of low income countries. With only physical shipping costs, Germany gains even more, while Poland loses more. But as we increase shipping costs (by a factor of six in line with recent increases suggested by Carriere-Swallow et al., 2022), the distributional impact becomes mitigated. If we raise shipping costs only for non-neighboring countries, the magnitude of the consumer surplus changes falls somewhere in between.[28]

6 Conclusion

Governments have taken various measures to remove non-tariff trade barriers and promote market integration. These measures often involve interventions against restrictive distribution practices set up by firms. The European Commission's ban on geo-blocking practices is a recent example, aiming to integrate online markets as part of the Single Digital Market program. In this paper, we develop a framework to evaluate the impact of such online market integration, taking into account possible spillover effects to traditional distribution channels. We adapt the standard random coefficients logit demand model to allow for substitution between multiple distribution channels and to incorporate

[27] We outline how we formally incorporate shipping costs in online Appendix A.4. We measure physical shipping costs across countries as parcel postage rates for weight categories between two and five kilograms (based on Meschi et al. (2013) and reported in Table A.11 of online Appendix A.2). We match these rates to the portable PC products based on their weight.

[28] As could be expected, the effects become smaller for even larger shipping costs, and almost vanish when raising them by a factor of twelve. We also considered a case where physical shipping costs are borne by the producer, and this gives similar conclusions.

Table 7: Counterfactual Outcomes by Country (with Shipping Costs)

	Pre-Integration Access (PIA)			
	ΔCS (mln euros)			
	$0 * \tau$	$1 * \tau$	$6 * \tau$	$1 * \tau_n$, $6 * \tau_{nn}$
BE	0.878	0.322	-0.666	0.129
DK	2.055	1.060	1.913	-0.618
F	8.197	0.905	-3.243	-1.041
D	15.67	28.85	10.61	13.72
UK	10.95	10.27	12.27	6.611
IT	-4.533	-5.857	-0.576	-0.589
NL	3.330	0.876	-2.560	-1.143
PO	-15.47	-17.12	-12.21	-18.55
SK	-3.995	-4.459	-4.578	-6.315
ES	-6.299	-7.675	-1.764	-10.10
All	10.78	7.181	-.808	-17.90

Note: Based on Adapted BLP (I). We use the shipping costs reported in Table A.11 of online Appendix A.2. The reported outcomes in the first column ($0 * \tau$) do not account for shipping costs, and are identical to the first column in the top panel of Table 5 in the main text. The remaining columns show the case of physical shipping costs ($1 * \tau_n$), six times higher shipping costs ($1 * \tau_n$), and six times higher shipping costs only for non-neigboring countries ($1 * \tau_n, 6 * \tau_{nn}$).

consumer arbitrage between multiple countries. We also show how to account for the presence of remaining shipping costs after integration.

We apply our framework to the European portable PC market, where geo-blocking restrictions were prevalent during our sample period and have recently been banned. We find that reducing cross-border arbitrage restrictions through a geo-blocking ban has considerable distributional effects. Consumers in high income countries gain much more, potentially at the expense of consumers in medium and low income countries. At the same time, a ban on geo-blocking has small effects on total EU welfare if it does not lead to more product choice. In other words, the price convergence effect that reduces third-degree price discrimination mainly redistributes surplus between different countries. However, after taking into account the product choice expansion effect, the ban on geo-blocking implies sizeable total consumer and welfare benefits, with annual gains of about 300 million Euro during our sample period. The benefits would be even larger because e-commerce continues to gain in popularity, and because the ban applies to a much broader set of retail categories than portable PCs.

We caution that our analysis is based on data that is aggregated across retailers. In future research, it would be interesting to obtain retail-level data to obtain further insights in the sources of cross-country differences in variety. It would also be interesting to collect data after the geo-blocking ban. This would provide an interesting validation opportunity to study whether price differences indeed decreased after 2018, or whether other cross-border trade barriers remain. Nevertheless, such an analysis is challenging because the portable PC market may be evolving rapidly for other reasons than the geo-blocking ban. The offline channel does not provide an obvious control group, because of substitution between both channels.

From a methodological perspective, we show that a straightforward application of the standard BLP demand model is not warranted in our setting. This entails a high-dimensional idiosyncratic taste valuation that is specific to both the distribution channel and country of purchase for each product. Such a model does not only generate unreasonable substitution patterns between sales channels, but also creates artificial product differentiation between countries as foreign markets open up. This model would imply implausibly high consumer welfare benefits and even profit gains from the opening up of foreign markets. The latter is inconsistent with the firms' revealed preference for deliberately keeping markets segmented before the geo-blocking ban. We show how our adapted BLP model addresses these issues, and can be estimated in a computationally feasible way.

We hope that our framework can be fruitfully applied in future work to evaluate the impact of increased market integration (or the absence of it) in a variety of other settings. More generally, the adapted BLP model may find applications in other settings where products or brands are sold under different variants that do not create new differentiation dimensions. For example, it may be particularly interesting to study firms' strategies of price discrimination through offering menus of different qualities without mixing unintended features of product differentiation.

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