ONLINE APPENDIX

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

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Abstract

This online appendix consists of four parts, referred to in the main text. Appendix A.1 provides additional industry background. Appendix A.2 provides additional tables and figures. Appendix A.3 discusses computational details, Appendix A.4 provides a formal outline of the counterfactuals.

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A Appendix

A.1 Additional Industry Background

This Appendix provides additional background on the portable PC market, with a discussion of the manufacturers, retailers, pricing and product availability in the traditional and online channel. Information on manufacturers is based on our main GfK dataset, while information on the retail structure is based on Euromonitor and some other sources.

The top seven laptop brands in our dataset are Acer, Apple, Asus, HP, Lenovo, Samsung and Toshiba. They have a combined market share of 78% in total sales of laptops between January 2012 and March 2015 in the group of ten countries: HP (17%), Asus (15%), Acer (14%), Lenovo (13%), Toshiba (9%), Apple (6%) and Samsung (5%) There is therefore a moderate concentration in the manufacturing of consumer electronics, which is dominated by international corporations from Asia and the U.S. The market is also very dynamic with market shares changing over time. These seven largest brands are present in all countries. Germany is the largest market for laptops in Europe and has the greatest variety of brands and products. The products available in Germany but not in other countries are in general local brands with smaller sales. There are also local products in other countries that are not available in Germany.

The distribution of consumer electronics in Europe is characterized by five independent European-level retailers and several national players, indicating a relatively limited role of direct-to-consumer retail. The five largest multinationals are Metro AG from Germany with revenues of 19.8 billion Euro as of 2015 in selected countries, Dixons Carphone Plc originating from the UK (10.2 billion Euro), Expert International GmbH from Switzerland (7.7 billion Euro), Euronics International Ltd with headquarter in the Netherlands (6.8 billion Euro) and Darty Plc from France (4 billion Euro). Altogether they account for 47% of sales of consumer electronics in selected European countries. Market shares of these retailers in the countries in our sample are shown in Table A.1 below. The remaining 53% of the market consists of a number of national players, which in general are present in one country only, as well as by a large number of small online and offline retailers.

Table A.1: Market shares of main consumer electronics retailers

	Metro	Euronics	Expert	Dixons	Darty
BE	14.0%	3.6%	0.0%	0.0%	6.0%
DK	0.0%	0.9%	8.1%	32.0%	0.0%
FR	0.0%	1.4%	0.0%	0.0%	16.5%
DE	46.0%	7.5%	22.2%	0.0%	0.0%
UK	0.0%	3.2%	0.0%	40.0%	0.0%
IT	19.0%	17.6%	15.5%	0.0%	0.0%
NL	40.0%	6.4%	3.9%	0.3%	6.8%
PL	23.0%	0.0%	0.0%	0.0%	0.0%
SK	0.0%	0.9%	1.9%	0.0%	0.0%
SP	35.0%	22.0%	0.0%	7.2%	0.0%

Source: Euromonitor.

Furthermore, there appear to be large differences in the number of brick-and-mortar outlets across countries. The most populous countries Germany, France and Italy had the greatest number of outlets in 2015, which were respectively 17,709, 17,324 and 11,641. The UK with a population comparable to France had a much lower number of outlets (8,210), while smaller Belgium had a greater number of outlets (5,559) than more populous Netherlands (3,357 outlets). The main retailer Metro AG had 761 outlets across selected countries. The numbers of outlets of the other four major retailers are as follows: Euronics International Ltd (6,057), Expert International GmbH (1,153), Dixons Carphone Plc (1,693) and Darty Plc (399). These outlets differ with respect to their size and the range of available products.

As discussed in the main text, we observe average transaction prices across products and distribution channels (defined as total product revenues in each channel divided by total sales over all retailers). GfK collects the data directly from the electronic point of sales systems from retailers and resellers, and estimates a coverage of 87% of total sales. As compared to prices collected by price checkers in retail outlets (i.e. data collected manually from price displays), the data is considered to offer a higher degree of accuracy and reliability, as it reflects the price actually paid rather than advertised. Although the price information is therefore very representative, we do not have systematic retailer-level price information. But using an online source, we verified that our prices are comparable to list prices.[1] Our analysis attributes cross-country price differences to country-specific pricing policies of the manufacturers, or more generally (as discussed in Section 4.4) as the result of the combined pricing strategies of manufacturers and retailers (of which several operate across different countries). In principle, it would also be interesting to disentangle the role

[1]We used website geizhals.de to find historical prices for selected laptop models sold online in Germany. The prices listed on this website are the lowest prices among listed online sellers. They are highly correlated with our prices with a coefficient of correlation of 0.98.

of manufacturers and retailers, but this would require retailer-level data. A few papers looked at pricing by the same retailer within and between different countries (e.g., Cavallo, 2017; Cavallo, Neiman and Rigobon, 2014; Gorodnichenko and Talavera, 2017), but they do not have information on offline prices, nor information on online or offline sales.

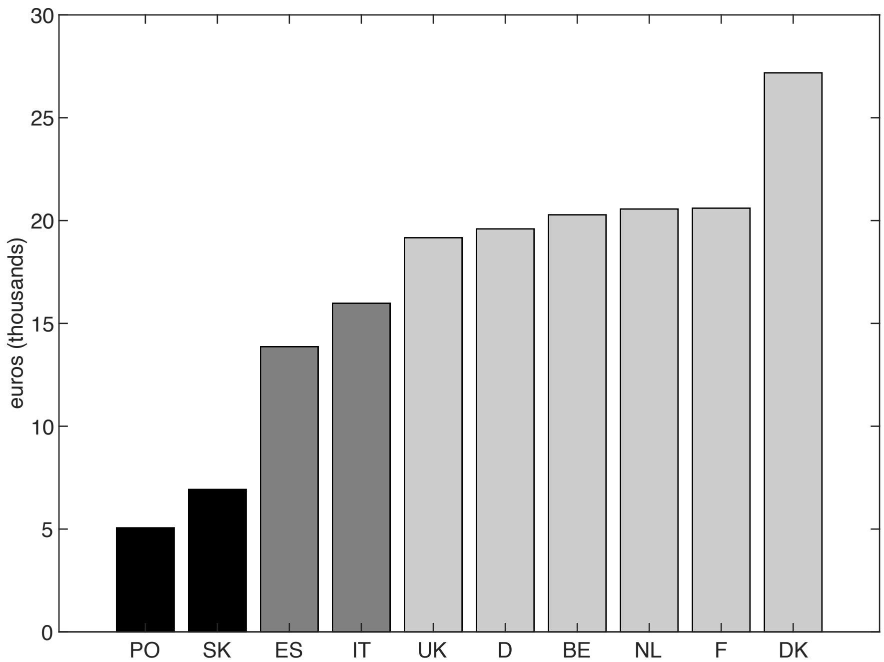
Although our data cannot distinguish between the separate role of manufacturers and retailers, they do provide interesting insights in their combined role, and specifically into differences between the traditional and online sales channel. In another paper, Duch-Brown et al. (2021), we document in more detail that cross-country price differences are comparable for the traditional and online sales channel, and that adjustments to shocks occur rather quickly, indicating that online markets are not more integrated than traditional markets.

Our data also provide information on product assortment. The majority of products tend to be more widely available in the traditional than in the online channel. This may seem to suggest that there is less online variety. However, as discussed above, there is a large number of brick-and-mortar stores (which may individually offer less variety than online stores). Furthermore, many products may be listed online but not actually sold. This is supported by the report from Ecorys (2011) prepared for the European Commission, which states: "The main role of online sales appears to be as an alternative sales channel for more popular product models also available through traditional (offline) retail stores rather than providing consumers with an extended choice of products. For the six countries covered by the detailed analysis of online markets, the overwhelming majority of online sales relates to models that are also available through traditional retail stores. Moreover, although there may be a substantial proportion of models that are found to be exclusive to only one of the sales channels (particularly for offline sales), these account for only a small proportion of total sales of either channel."

A.2 Additional Tables and Figures

A.2.1 Data

Figure A.1: Median income levels



Note: Based on average median incomes over the sample period. The countries are coded as follows: Belgium (BE), Denmark (DK), France (F), Germany (D), Italy (IT), the Netherlands (NL), Poland (PO), Slovakia (SK), and Spain (ES).

A.2.2 Empirical Results

Table A.2: First-Stage Regressions

	(I)	(II)	(III)	(IV)	(V)
$z_{Weight,same}$	**-.1522**	**-.1448**	**-.1478**	**-.1228**	**-.1418**
	(.0531)	(.0518)	(.0518)	(.0392)	(.0393)
$z_{Diagonal,same}$	**.1363**	**.1064**	**.1119**	**.1674**	**.1982**
	(.0820)	(.0800)	(.0800)	(.0597)	(.0598)
$z_{Resolution,same}$	**-.0135**	**-.0014**	**-.0026**	**-.0628**	**-.0758**
	(.0372)	(.0363)	(.0364)	(.0268)	(.0268)
$z_{Weight,other}$	**-1.309**	**-1.374**	**-1.361**	**-.3978**	**-.3902**
	(.0622)	(.0607)	(.0609)	(.0440)	(.0443)
$z_{Diagonal,other}$	**1.602**	**1.714**	**1.691**	**.5894**	**.5765**
	(.0956)	(.0933)	(.0936)	(.0654)	(.0660)
$z_{Resolution,other}$	**-.3641**	**-.4376**	**-.4238**	**-.2508**	**-.2482**
	(.0441)	(.0431)	(.0432)	(.0291)	(.0293)
$z_{freight,diagonal}$	-	-	-	-	**.1250**
					(.0366)
$z_{freight,weight}$	-	-	-	-	**-1.240**
					(.1958)
$z_{freight,diagonal*weight}$	-	-	-	-	**1.114**
					(.1686)
Common Trend	x	x	x	x	x
Country FE	-	x	x	x	x
Month FE	-	-	x	x	x
Product FE	-	-	-	x	x
Online Trends	-	-	-	x	x
R^2	.684	.699	.700	.904	.904
F-statistic	173	182	182	20.3	18.6

Note: Based on 10 288 sample observations. Standard errors are shown in parentheses. Observed characteristics are included in all regressions. The F-statistic is computed for the subset of excluded instruments. Column (V) adds three cost shifters to the instruments: airfreight rates from Asia to Europe (proxied by airfreight rates from South Korea to the UK that we obtained from Bloomberg), multiplied by the diagonal of each laptop, its weight and the product of diagonal and weight.

Table A.3: Demand Estimates - Price and Characteristics

	Logit	Adapted Logit	BLP (I)		Adapted BLP (I)	
			mean	std. dev.	mean	std. dev.
α_L	**.0061**	**.0072**	**.0068**		**.0069**	
	(.0008)	(.0008)	(.0011)		(.0014)	
α_M	**.0054**	**.0064**	**.0058**		**.0059**	
	(.0007)	(.0008)	(.0010)		(.0013)	
α_H	**.0039**	**.0048**	**.0043**		**.0044**	
	(.0007)	(.0007)	(.0009)		(.0012)	
Online				**7.561**		**8.982**
				(2.541)		(2.507)
CPU speed (GHz)	**.5455**	**.6091**	**.8583**		**.8608**	
	(.1231)	(.1290)	(.1970)		(.2005)	
RAM (GB)	**.0425**	**.0534**	**-.2070**	**.2524**	**-.2134**	**.2431**
	(.0089)	(.0093)	(.1026)	(.0675)	(.1280)	(.0810)
Weight (kg)	**-.0962**	**-.1440**	**-.2593**		**-.3094**	
	(.1456)	(.1527)	(.1759)		(.1927)	
Diagonal (inch)	**.1152**	**.1329**	**.1545**		**.1598**	
	(.0228)	(.0239)	(.0314)		(.0338)	
Resolution (PPI)	**.9356**	**1.138**	**1.290**	**.0060**	**1.294**	**.0973**
	(.2553)	(.2676)	(.4000)	(9.166)	(.7398)	(7.881)
Constant	**-11.19**	**-7.854**	**-8.399**		**-8.417**	
	(1.245)	(.8752)	(1.112)		(1.360)	
Trend	**-.0877**	**-.0777**	**-.0918**		**-.0869**	
	(.0071)	(.0075)	(.0151)		(.0127)	

Note: Based on 10 288 observations. Standard errors are shown in parentheses. The second and fourth specification are the parameter estimates of Adapted Logit and Adapted BLP (I), as also shown in Table 4 in the main text. The first and fourth specification are the parameter estimates of Standard Logit and Standard BLP (I).

Table A.4: Demand Estimates - Online Means and Trends

	Logit		Adapted Logit		BLP (I)		Adapted BLP (I)	
	mean	trend	mean	trend	mean	trend	mean	trend
BE	**-2.083**	**.0548**	**.4812**	**-.0165**	**-13.24**	**.1944**	**-15.90**	**.2022**
	(.1618)	(.0172)	(.1696)	(.0180)	(4.516)	(.0406)	(4.638)	(.0906)
DK	**-.7621**	**.0054**	**.1957**	**-.0086**	**-6.928**	**.0123**	**-8.170**	**-.0029**
	(.1112)	(.0123)	(.1165)	(.0129)	(2.488)	(.0253)	(2.826)	(.0402)
F	**-1.135**	**.0200**	**.5873**	**-.0571**	**-9.408**	**.0852**	**-11.34**	**.0867**
	(.1316)	(.0144)	(.1379)	(.0151)	(3.556)	(.0257)	(3.838)	(.0263)
D	**-.6450**	**.0229**	**.1173**	**-.0010**	**-7.127**	**.0867**	**-8.524**	**.0928**
	(.1024)	(.0115)	(.1073)	(.0120)	(2.679)	(.0195)	(2.952)	(.0226)
UK	**-.9061**	**.0521**	**.3511**	**-.0226**	**-8.266**	**.2518**	**-9.857**	**.2878**
	(.1121)	(.0124)	(.1174)	(.0130)	(3.103)	(.0778)	(3.121)	(.0699)
IT	**-1.653**	**.0077**	**1.239**	**-.0583**	**-12.97**	**.0567**	**-15.79**	**.0375**
	(.1793)	(.0197)	(.1880)	(.0206)	(4.998)	(.0363)	(4.614)	(.0335)
NL	**-1.243**	**.0608**	**.1974**	**-.0071**	**-8.942**	**.2478**	**-10.59**	**.2812**
	(.1166)	(.0126)	(.1222)	(.0133)	(3.128)	(.0620)	(3.147)	(.0602)
PO	**-1.368**	**.0090**	**.5935**	**-.0533**	**-10.13**	**.0790**	**-12.20**	**.0775**
	(.1398)	(.0148)	(.1465)	(.0155)	(3.688)	(.0285)	(3.534)	(.0282)
SK	**-.8221**	**.0824**	**-.0680**	**.0312**	**-7.693**	**.2560**	**-9.303**	**.2933**
	(.1189)	(.0132)	(.1246)	(.0138)	(3.016)	(.0706)	(3.004)	(.0641)
ES	**-2.496**	**.1168**	**.2710**	**.0237**	**-14.23**	**.3571**	**-17.13**	**.3986**
	(.1490)	(.0169)	(.1561)	(.0177)	(4.876)	(.0834)	(4.822)	(.1148)

Note: Based on 10 288 observations. Standard errors are shown in parentheses. This table is a continuation of Table A.3 on the previous page.

Table A.5: Marginal Cost Regressions

	Common Online Cost			Country-Specific Online Cost		
		Traditional	Online		Traditional	Online
CPU speed	**.3710**			**.3730**		
RAM	**.0133**			**.0123**		
Weight	**-.1141**			**-.1028**		
Diagonal	**.0358**			**.0353**		
Resolution	**.6438**			**.6532**		
Constant	**-1.617**			**-1.630**		
Online Trend	**.0002**			**-.0001**		
Trend	**-.0227**			**-.0222**		
BE		**0**	**-.1802**		**0**	**-.1094**
DK		**.0751**	**-.1802**		**.0775**	**.0092**
F		**-.3298**	**-.1802**		**-.3300**	**-.4011**
D		**-.1815**	**-.1802**		**-.1821**	**-.2366**
UK		**-.2651**	**-.1802**		**-.2647**	**-.2389**
IT		**-.1480**	**-.1802**		**-.1476**	**-.1420**
NL		**-.1323**	**-.1802**		**-.1313**	**-.1582**
PO		**-.1166**	**-.1802**		**-.1174**	**-.2094**
SK		**-.1476**	**-.1802**		**-.1475**	**-.1778**
ES		**-.1326**	**-.1802**		**-.1309**	**-.0903**
R^2	**.8943**			**.8988**		

Note: Based on 10 288 observations and Adapted BLP (I). Traditional distribution channel in Belgium is base category. The specifications also include product and month-of-year fixed effects. To preserve space, we do not report the standard errors, but summarize the significance pattern as follows. For the common online cost specification, except for the online trend, all estimated coefficients are statistically significant at the 95 percent confidence level. For the country-specific online cost specification, except for the online trend and the online intercept for Denmark, all coefficients are statistically significant at the 95 percent confidence level.

A.2.3 Empirical Results - Extensions

Table A.6: Demand Estimates with Alternative Instruments

	Logit, OLS	Logit, IV(1)	Logit, IV(2)	BLP (I), IV(1)		BLP (I), IV(2)	
	mean	mean	mean	mean	std. dev.	mean	std. dev.
α_L	**.0017**	**.0061**	**.0056**	**.0068**		**.0058**	
	(.0001)	(.0008)	(.0007)	(.0011)		(.0008)	
α_M	**.0011**	**.0054**	**.0049**	**.0058**		**.0050**	
	(.0001)	(.0007)	(.0006)	(.0010)		(.0007)	
α_H	**.0005**	**.0039**	**.0035**	**.0043**		**.0035**	
	(.0001)	(.0007)	(.0006)	(.0009)		(.0007)	
Online					**7.561**		**4.255**
					(2.541)		(1.832)
CPU Speed	**.1294**	**.5455**	**.4976**	**.8583**		**.6391**	
	(.0885)	(.1231)	(.1134)	(.1970)		(.1444)	
RAM	**.0243**	**.0425**	**.0404**	**-.2070**	**.2524**	**-.0962**	**.1654**
	(.0077)	(.0089)	(.0085)	(.1026)	(.0675)	(.0765)	(.0502)
Weight	**.0225**	**-.0962**	**-.0861**	**-.2593**		**-.1552**	
	(.1350)	(.1456)	(.1432)	(.1759)		(.1529)	
Diagonal	**.0740**	**.1152**	**.1106**	**.1545**		**.1282**	
	(.0201)	(.0228)	(.0221)	(.0314)		(.0260)	
Resolution	**.0511**	**.9356**	**.8358**	**1.290**	**.0060**	**.9779**	**-.0486**
	(.1827)	(.2553)	(.2354)	(.4000)	(9.166)	(.4922)	(9.985)
Constant	**-6.207**	**-7.505**	**-7.375**	**-8.399**		**-7.735**	
	(.7526)	(.8350)	(.8147)	(1.112)		(1.023)	
Trend	**-.0610**	**-.0877**	**-.0846**	**-.0918**		**-.0829**	
	(.0047)	(.0071)	(.0065)	(.0151)		(.0092)	
Wald Stat.	-	-	-	23.16		41.60	
Crit. Value				11.34		11.34	
$\overline{\eta}_{jj}$	-0.62	-3.46	-3.13	-3.75		-3.15	
# $\eta_{jj} > -1$	8,752	0	0	0		0	

Note: Based on 10 288 observations. Standard errors are shown in parentheses. Columns labeled by IV(1) employ the set of instruments used throughout the main text. Columns labeled by IV(2) add three cost shifters to the instruments used in IV(1): airfreight rates from Asia to Europe multiplied by the diagonal of each laptop, its weight and the product of diagonal and weight. For both specifications, the excluded instruments are interacted with country group dummies, so that the IV matrix is block diagonal. For both sets of excluded instruments the null hypothesis of weak instruments in the first-stage regressions can be rejected at confidence levels above 99 percent. The critical value for the Wald statistic applies to a 99 percent confidence interval 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 BLP model estimation. The price coefficients vary between three country groups that are color coded in Figure A.1. All specifications include a full set of product fixed effects and country-specific linear trends that are interacted with the online channel dummy.

Table A.7: Demand Estimates with Quarterly Aggregated Data

	OLS-Logit	IV-Logit	BLP (I)	
	mean	mean	mean	std. dev.
α_L	**.0020**	**.0068**	**.0073**	
	(.0001)	(.0008)	(.0013)	
α_M	**.0014**	**.0057**	**.0058**	
	(.0001)	(.0007)	(.0012)	
α_H	**.0007**	**.0043**	**.0044**	
	(.0001)	(.0007)	(.0011)	
Online				**9.474**
				(3.180)
CPU Speed	**.1849**	**.5974**	**.9116**	
	(.0855)	(.1158)	(.2002)	
RAM	**.0423**	**.0588**	**-.2288**	**.2796**
	(.0083)	(.0093)	(.1357)	(.0855)
Weight	**.0468**	**-.1085**	**-.3358**	
	(.1312)	(.1426)	(.1881)	
Diagonal	**.0816**	**.1326**	**.1843**	
	(.0197)	(.0229)	(.0341)	
Resolution	**-.0981**	**.9078**	**1.050**	**.1159**
	(.1772)	(.2614)	(.8992)	(8.238)
Constant	**-9.021**	**-10.80**	**-12.09**	
	(.7380)	(.8419)	(1.428)	
Trend	**-.0622**	**-.0928**	**-.1022**	
	(.0045)	(.0073)	(.0194)	
Wald Stat.	-	-	47.35	
Crit. Value			11.34	
$\overline{\eta}_{jj}$	-.80	-3.79	-3.85	
$\#\ \eta_{jj} > -1$	8,479	0	0	

Note: Based on 11 225 observations obtained by aggregating monthly data to the quarterly frequency. Standard errors are shown in parentheses. The specification and instruments are identical to those employed in the main model (see Table 4 and Table A.4).

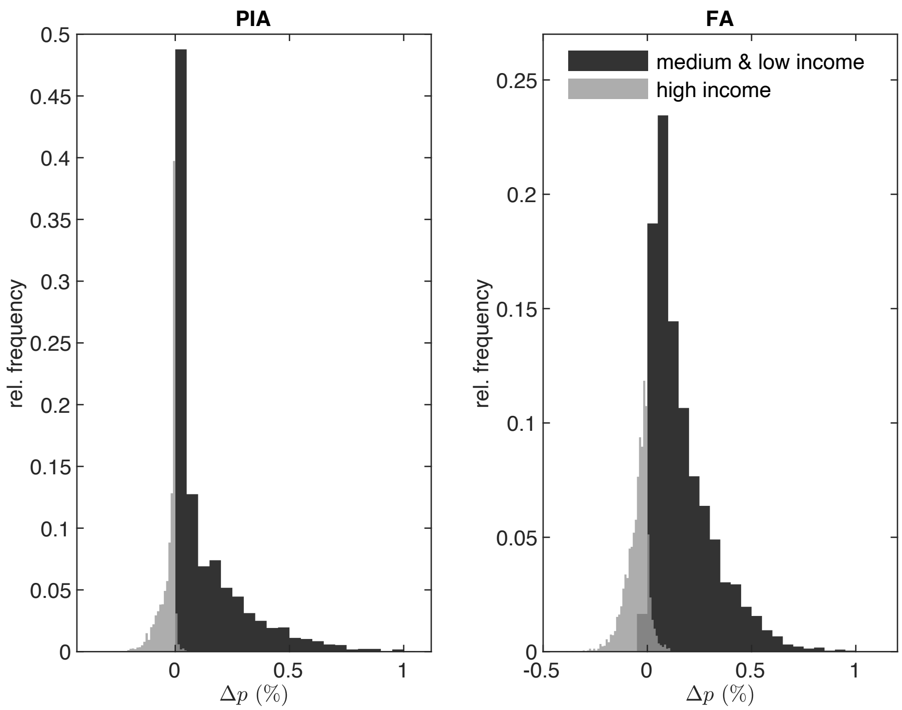
Table A.8: Demand Estimates with Disaggregated Product Data

	OLS-Logit	IV-Logit	BLP (I)	
	mean	mean	mean	std. dev.
α_L	**.0012**	**.0045**	**.0043**	
	(.0000)	(.0003)	(.0003)	
α_M	**.0009**	**.0039**	**.0036**	
	(.0000)	(.0003)	(.0003)	
α_H	**.0006**	**.0031**	**.0028**	
	(.0000)	(.0002)	(.0003)	
Online				**9.845**
				(2.157)
CPU Speed	**.0311**	**.6632**	**.6073**	
	(.0214)	(.0624)	(.0739)	
RAM	**.0450**	**.1039**	**.0978**	**.0163**
	(.0033)	(.0063)	(.0370)	(.2394)
Weight	**-.1792**	**-.0876**	**-.1108**	
	(.0310)	(.0340)	(.0474)	
Diagonal	**.0301**	**.0088**	**.0124**	
	(.0049)	(.0056)	(.0092)	
Resolution	**.0784**	**1.867**	**1.713**	**.0710**
	(.0543)	(.1719)	(.3537)	(3.488)
Constant	**-7.319.**	**-7.943**	**-8.111**	
	(.1753)	(.1933)	(.4233)	
Trend	**-.0875**	**-.1290**	**-.1315**	
	(.0022)	(.0045)	(.0056)	
Wald Stat.	-	-	22.58	
Crit. Value			11.34	
$\overline{\eta}_{jj}$	-.565	-2.68	-2.48	
# $\eta_{jj} > -1$	45 277	0	0	

Note: Based on 48 696 observations, with a more disaggregate product definition based on model names, as discussed in the text. Standard errors are shown in parentheses. The specification and instruments are identical to those employed in the main model (see Table 4 and Table A.4).

A.2.4 Counterfactuals

Figure A.2: Counterfactual Price Changes in the Traditional Distribution Channel



Note: This Figure complements the top part of Figure 5 in the main text (which considered the online distribution channel). 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.

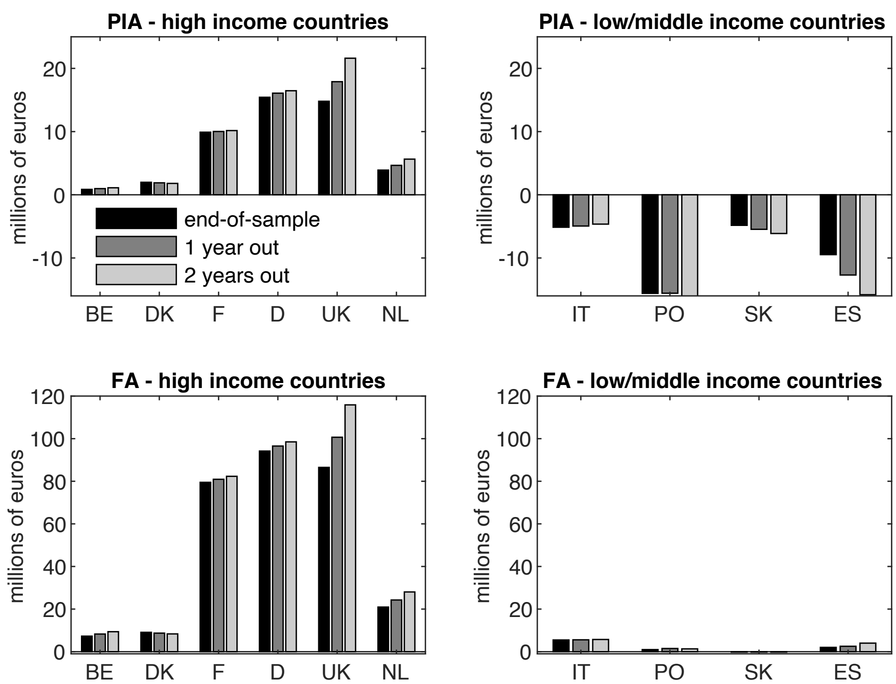
A.2.5 Counterfactuals - Extensions

Table A.9: Counterfactual Outcomes: Total Effects across Countries (Standard BLP)

	Pre-Integration Access (PIA)	Full Access (FA)
ΔCS	2285	2492
$\Delta\Pi$	326.8	338.5
ΔQ (%)	7.83	8.61
ΔQ_{trad} (%)	-6.74	-7.34
ΔQ_{on} (%)	50.8	55.7

Note: Based on Standard BLP (I) specification, for a comparison with Adapted BLP (I) specification shown in Table 6 in the main text. Changes in consumer surplus and changes in profits are measured in millions of euros per year.

Figure A.3: Counterfactual Consumer Surplus Changes (Future Years)



Note: Based on Adapted BLP (I), as an extension of the bottom part of Figure 5 (within-sample averages). The first bar shows the effect in the latest period in the sample; the next two bars are extrapolated effects one year and two years out of sample, based on the estimated common and online trend effects.

Table A.10: Counterfactual Outcomes: Total Effects across Countries (Future Years)

	In-Sample		One Year Out		Two Years Out	
	PIA	FA	PIA	FA	PIA	FA
ΔCS	10.8	298.2	12.9	318.8	14.1	341.0
$\Delta\Pi$	-10.9	8.46	-12.5	22.3	-13.9	23.2
ΔQ (%)	-.02	.97	-.04	1.73	-.06	2.01
ΔQ_{trad} (%)	.03	-.75	.04	-.86	.05	-.91
ΔQ_{on} (%)	-.16	6.02	-.15	5.37	-.19	5.12

Note: Based on Adapted BLP (I). PIA and FA refer to the scenarios of Pre-Integration Availability and Full Availability. Changes in consumer surplus and changes in profits are measured in millions of euros per year. The In-Sample results are identical to those reported in Table 6 in the main text. The One Year Out and Two Year Out are extrapolated effects one year and two years out of sample, based on estimated common and online trend effects.

Table A.11: Bilateral Parcel Shipping Costs

	BE	DK	F	D	UK	IT	NL	PO	SK	ES
BE	5.70	30	15	15	15	30	15	30	30	30
DK	30.75	10.07	30.75	28.60	30.75	30.75	30.75	30.75	30.75	30.75
F	12	15.45	7.51	12	14.50	14.50	12	19.50	19.50	14.50
D	17	17	17	6.90	17	17	17	17	17	17
UK	42.28	46.85	46.85	46.85	12.63	49.98	42.28	57.60	57.60	49.98
IT	34	34	34	34	34	11.40	34	34	34	34
NL	14.30	14.30	14.30	14.30	14.30	14.30	8.05	19.80	14.30	14.30
PO	20.61	20.61	20.61	20.61	20.61	20.61	20.61	4.27	20.61	20.61
SK	19	19	19	19	19	19	19	19	2.80	19
ES	30.26	30.26	30.26	30.26	30.26	30.26	30.26	30.85	30.26	6.60

Note: The rates are measured in euros by Meschi et al. (2013) and apply to all parcels with weights between two and five kilograms. Where both economy and priority shipping rates are available, we use the priority rates. Express shipping rates are not used.

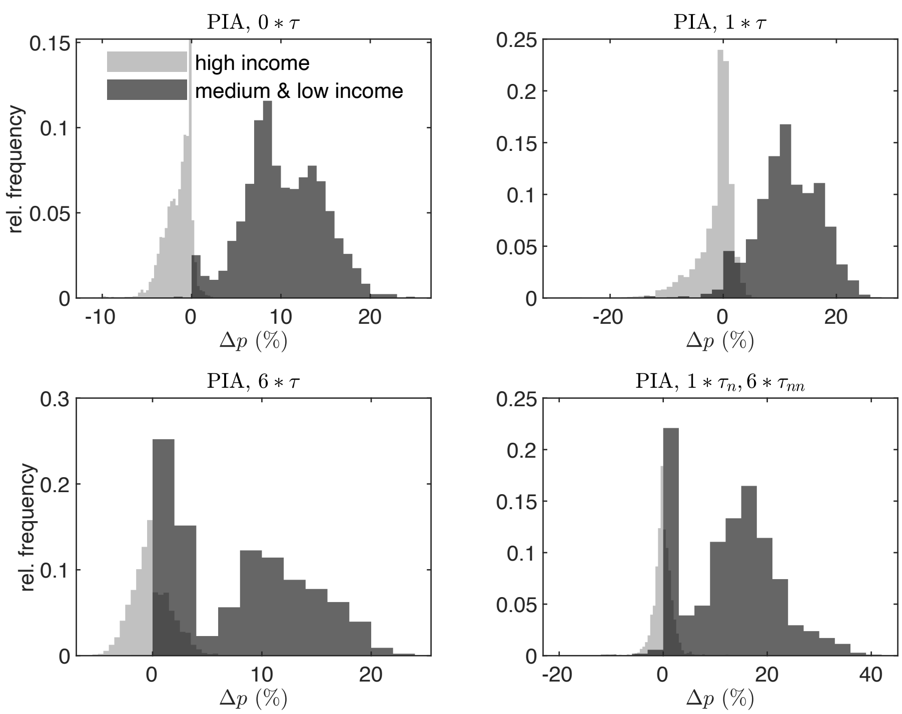


Figure A.4: Counterfactual Online Price Changes (with shipping costs)

Note: Based on Adapted BLP (I). We use the shipping costs reported in Table (A.11). The reported outcomes in the top left plot ($0*\tau$) do not account for shipping costs, and are identical to the top left plot of Figure 5 in the main text). The remaining plots 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-neighboring countries ($1*\tau_n, 6*\tau_{nn}$).

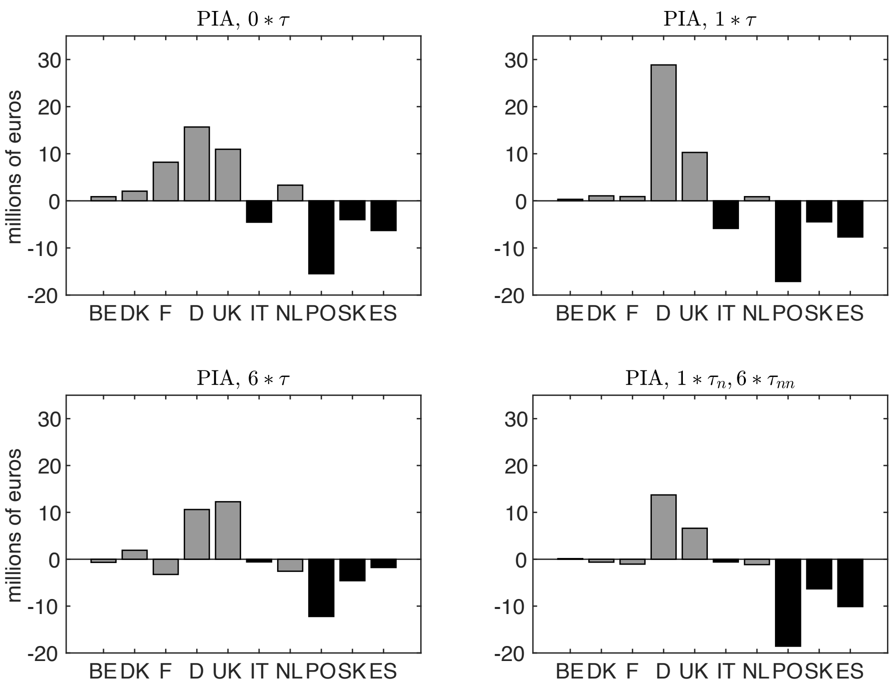


Figure A.5: Counterfactual Consumer Surplus Changes (with Shipping Costs)

Note: Based on Adapted BLP (I). The reported outcomes in the top left plot ($0 * \tau$) do not account for shipping costs, and are identical to the bottom left plot of Figure 5 in the main text). The remaining plots 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-neighboring countries ($1 * \tau_n, 6 * \tau_{nn}$).

A.3 Computational Appendix

We provide further computational details in the following three subsections. First, we derive the adapted BLP model as a limiting case of the random coefficients nested logit model. Second, we discuss the inversion of aggregate shares in our estimation. The inversion is considerably slowed down by setting the nesting parameter close to 1. We effectively reduce the increase in computational cost by using a globally convergent Anderson Type-I fixed point acceleration scheme. Third, we provide diagnostics on both our BLP and adapted BLP model estimations.

A.3.1 Approximation of the Adapted BLP Model

As discussed in the main text, we approximate the adapted BLP model with a random coefficients nested logit model, where each product j is a nest containing two alternatives: the traditional and online sales channel. The individual-specific taste parameter in such a set-up is $\varepsilon_{i,j} + (1-\rho)\varepsilon_{i,jk}$ (Berry, 1994), where $\rho \in (0,1)$ is a nesting parameter measuring the extent of preference correlation for the two channels within the product nest. It covers both the standard BLP model ($\rho = 0$) and the adapted BLP model ($\rho \to 1$) as special cases. Hence, to estimate the adapted BLP model we can estimate the random coefficients nested logit model by imposing ρ sufficiently high.

The random coefficient nested logit choice probability (conditional on β_i) for a product j and channel k is equal to

$$s_{jk}(\beta_i) = \int_{-\infty}^{\infty} s_{k|j}(\beta_i, \nu^O) s_j(\beta_i, \nu^O) dF(\nu^O),$$

where

$$\begin{aligned} s_{k|j}(\beta_i, \nu^O) &= \frac{\exp\left(V_{i,jk}/\left(1-\rho\right)\right)}{\sum\limits_{k' \in \{T,O\}} \exp\left(V_{i,jk'}/\left(1-\rho\right)\right)} \\ s_j(\beta_i, \nu^O) &= \frac{\exp\left(I_{i,j}\right)}{1 + \sum\limits_{j' \in \mathcal{J}_k} \exp\left(I_{i,j'}\right)}, \end{aligned}$$

$V_{i,jk} = V_{jk}(\beta_i, \nu^O)$ and $I_{i,j} = I_j(\beta_i, \nu^O)$ is the so-called "inclusive value" defined as

$$I_{i,j} = (1-\rho) \ln \left(\sum_{k' \in \{T,O\}} \exp\left(V_{i,jk'}/\left(1-\rho\right)\right) \right).$$

As $\rho \to 1$, we have $I_{i,j} \to \max\{V_{i,jT}, V_{i,jO}\}$ and $s_{k|j}(\mu_{ij}, \nu^O) \to \mathbf{1}(V_{i,jk} = \max\{V_{i,jT}, V_{i,jO}\})$. We can then write the probability as

$$s_{jk}(\beta_i) = \int_{-\infty}^{\infty} \mathbf{1}(V_{i,jk} = \max\{V_{i,jT}, V_{i,jO}\}) \frac{\exp\left(\max\{V_{i,jT}, V_{i,jO}\}\right)}{1 + \sum\limits_{j' \in \mathcal{J}_k} \exp\left(\max\left\{V_{i,j'T}, V_{i,j'O}\right\}\right)} dF(\nu^O).$$

For channel $k = T, O$, we can write this as

$$\begin{aligned} s_{jT}(\beta_i) &= \int_{-\infty}^{\infty} \mathbf{1}(\nu_i^O \leq \Delta_j) \frac{\exp\left(\max\{V_{i,jT}, V_{i,jO}\}\right)}{1 + \sum\limits_{j' \in \mathcal{J}_k} \exp\left(\max\left\{V_{i,j'T}, V_{i,j'O}\right\}\right)} dF(\nu^O) \\ s_{jO}(\beta_i) &= \int_{-\infty}^{\infty} \mathbf{1}(\nu_i^O > \Delta_j) \frac{\exp\left(\max\{V_{i,jT}, V_{i,jO}\}\right)}{1 + \sum\limits_{j' \in \mathcal{J}_k} \exp\left(\max\left\{V_{i,j'T}, V_{i,j'O}\right\}\right)} dF(\nu^O), \end{aligned}$$

Using the ordering $\Delta_1 \leq ...\Delta_{j-1} \leq \Delta_j \leq \Delta_{j+1} \leq ... \leq \Delta_J$, we can break up the integral in parts to obtain the expressons in the main text, namely

$$\begin{aligned} s_{jT}(\mu_{ij}) &= \int_{-\infty}^{\Delta_1} \frac{\exp\left(V_{i,jT}\right)}{1 + D_{i,1}} dF(\nu^O) + \int_{\Delta_1}^{\Delta_2} \frac{\exp\left(V_{i,jT}\right)}{1 + D_{i,2}} dF(\nu^O) + ... + \int_{\Delta_{j-1}}^{\Delta_j} \frac{\exp\left(V_{i,jT}\right)}{1 + D_{i,j}} dF(\nu^O) \\ s_{jO}(\mu_{ij}) &= \int_{\Delta_j}^{\Delta_{j+1}} \frac{\exp\left(V_{i,jO}\right)}{1 + D_{i,j+1}} dF(\nu^O) + ... + \int_{\Delta_{J-1}}^{\Delta_J} \frac{\exp\left(V_{i,jO}\right)}{1 + D_{i,J}} dF(\nu^O) + \int_{\Delta_J}^{\infty} \frac{\exp\left(V_{i,jO}\right)}{1 + D_{i,J+1}} dF(\nu^O). \end{aligned}$$

where the terms $D_{i,j}$ (for $j = 1, ...J + 1$) are given by the expressions in the last column of Table 3.

A.3.2 Aggregate Share Inversion in the Random Coefficient Nested Logit Model

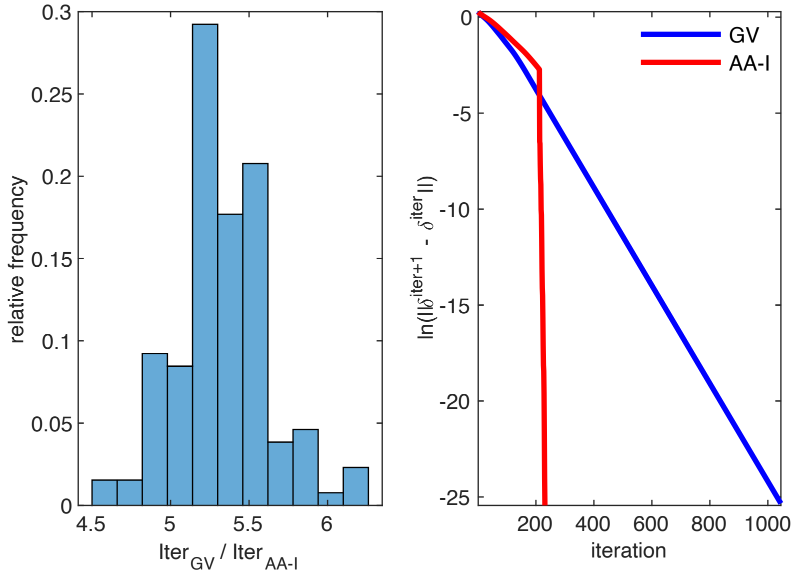
The main advantage of approximating the adapted BLP model through the random coefficients nested logit model is that the market share system is smooth in the parameters and can be inverted through a contraction mapping. More specifically, Grigolon and Verboven (2014) show that the traditional BLP contraction mapping can be applied, provided that the update to mean utilities at each iteration of the fixed point is damped by $(1-\rho)$:

$$\delta_{jk}^{iter+1} = \delta_{jk}^{iter} + (1-\rho)\ln\left(\frac{\mathcal{S}_{jk}}{s_{jk}(\delta^{iter};\widehat{\theta})}\right) \tag{A.1}$$

Approximating the adapted BLP model closely requires us to set ρ as high as possible. However, as $\rho \to 1$, the contraction mapping becomes weak and this considerably slows down the convergence of the fixed point. Hence, compared to a BLP model, many more iterations are required to obtain the vector of mean utilities that matches the observed and model-implied aggregate market shares. To counteract this increase in computational burden, we apply the globally convergent fixed point acceleration scheme of Zhang, O'Donoghue and Boyd (2020). The approach preserves the global contraction property of the BLP fixed point, while convergence of the accelerated fixed point is no longer guaranteed to be monotonic. The method stores the outcomes of a fixed number of iterations and uses these outcomes to approximate the Jacobian of the nonlinear equation system at low computational cost. If the quality of the approximation is sufficiently good, the iteration takes an approximate Newton step. Otherwise, the damped iteration, equation (A.1), is used. In practice, we find that the acceleration scheme is highly effective and reduces the required number of iterations to convergence by a factor of roughly five, and the computational runtime of the inversion by a factor of three. Figure A.6 plots the convergence path for the damped fixed point (GV) and the accelerated scheme (AA-I) at $\rho = 0.9$.

A practical question is how close ρ should be to 1 to have a reasonable approximation of the adapted BLP model. Picking large values makes the approximation more accurate, but may also lead to numerical difficulties and slow down the contraction mapping. Specifically, we set $\rho = 0.9$. For higher values of ρ we experienced numerical difficulties, because we obtain numbers that exceed the limits of double precision floating point arithmetic. To assess how well we approximate the adapted BLP model with $\rho = 0.9$, we evaluate the aggregate market share function of our adapted BLP model (11) at the estimated parameter vector of the nested logit random coefficients model with $\rho = 0.9$. Figure A.7 shows the distribution of the resulting net relative deviations between the two aggregate market share vectors. The deviations are most often very small. Almost all observations have a relative deviation of less than one percent in absolute value, and most often the deviations are much smaller. We therefore conclude that setting $\rho = 0.9$ is a sufficiently accurate approximation of the adapted BLP model for our purposes.

Figure A.6: Iterations Until Convergence: Damped BLP Contraction versus Globally Convergent Type-I Anderson Acceleration



Note: The left panel shows the relative frequency histogram for the two approaches' ratio of iterations until convergence, while the right panel plots the convergence path for the two share inversion schemes evaluated at the coefficient vector that corresponds with the each model's global minimum candidate. GV stands for Grigolon-Verboven and the iteration is given by equation (A.1). AA-I denotes the globally convergent Anderson Acceleration Type-I scheme of Zhang, O'Donoghue and Boyd (2020). The drop off around 200 iterations for AA-I actually contains several iterations, which is visually imperceptible due to the scale of the x-axis.

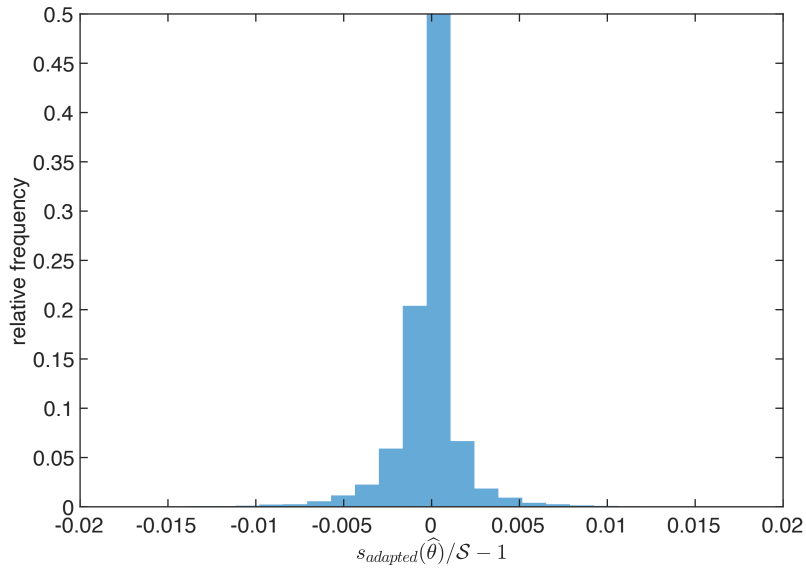
A.3.3 Diagnostics

The estimation of the BLP and adapted BLP (or parameterized random coefficient nested logit) models are based on 1 000 modified latin hypercube sampling (MLHS) draws and 30 randomly drawn initial iterates for the nonlinearly entering parameters, $\theta_2^{blp/rcnl} = (\sigma_{on}, \sigma_{RAM}, \sigma_{ppi})'$. To approximate the adapted BLP model closely, we parameterize the nesting coefficient in the random coefficient nested logit model to $\rho = 0.9$. Our BLP estimation routine returns either the positive or negative square root of the squared entries in θ_2. We restrict the estimates of the entries in θ_2^{rcnl} to be positive, because allowing for $-\sqrt{\sigma_{on}^2}$ changes the sign of the cutoffs in the adapted BLP model, which unnecessarily complicates the computation of the model-implied aggregate shares.[2]

The inner convergence tolerance is set to 10^{-11} for inverting the aggregate market shares and we use a trust region optimizer with analytical gradients to minimize the nonlinear GMM-IV objective functions for both models. An extreme value of the objective function is classified as a local minimum if the norm of the gradient is close to zero and the objective function's Hessian is

[2]In the BLP model, $-\sqrt{\theta_{2,k}^2}$ is equivalent to $\sqrt{\theta_{2,k}^2}$ as long as the distribution of ν is symmetric around zero, which holds for $\nu_{ik} \sim N(0,1)$, and the number of simulation draws is large.

Figure A.7: Share Deviations - Adapted BLP versus Random Coefficients Nested Logit with $\rho = 0.9$



Note: s denotes the aggregate shares obtained from (6) and (7) at the estimated random coefficients nested logit parameter vector, $\widehat{\theta}$. S denotes the observed aggregate share vector, which the estimated approximate adapted BLP model matches very closely.

positive definite. For the BLP and adapted BLP estimations, the coefficients of variation of the local minima are 1.21 and 1.42 percent, respectively. The tight clustering of the local minima is evidence that the propagation of simulation error in the objective functions is bounded, so that the estimators yield consistent and asymptotically normal estimates (see Berry, Linton and Pakes (2004)).

As Brunner et al. (2017) show, variation in local minima that is due to simulation error can yield substantial variation in model-implied economic outcomes. To evaluate whether the remaining variation between local minima is economically important, we compute the own-price elasticities for all observations in the sample for all local minima. Table (A.12) reports the outcomes. Pooling the model-implied own-price elasticities for all local minima, the bold figures represent the average value of the own-price elasticity at the given percentile. The figures in square brackets are the corresponding minimum and maximum values. Clearly, there is very little variation in the elasticities across all the minima. This holds along the entire distribution of elasticities and for both the BLP and adapted BLP estimations. We conclude that our estimates are not affected by the propagation of simulation error in the GMM-IV objectives in any economically meaningful way.

Table A.12: Model-Implied Own-Price Elasticity Distributions of All Local Minima

	percentiles				
	1[st]	25[th]	median	75[th]	99[th]
BLP	**-8.77**	**-4.53**	**-3.35**	**-2.57**	**-1.75**
	[-8.96, -8.65]	[-4.66, -4.43]	[-3.44, -3.27]	[-2.65, -2.51]	[-1.81, -1.71]
adapted	**-9.34**	**-4.79**	**-3.56**	**-2.73**	**-1.83**
BLP	[-9.66, -9.06]	[-4.96, -4.66]	[-3.69, -3.46]	[-2.84, -2.65]	[-1.91, -1.77]

Note: The average values of the own-price elasticity between all local minima is reported in bold. The minimum and maximum values of the own-price elasticity at the respective percentiles is reported in square brackets.

A.4 Post-integration Equilibrium: Formal Analysis

This Appendix provides a more detailed formal analysis of the post-integration equilibrium outlined in section 5.1. To simplify notation, we remove the time subscript t.

Segmented markets Under nationally segmented markets, consumers can buy products only in their own country. Hence, the market shares (11) depend only on the price vector in the consumers' own country, i.e. $s_{c,jkc}(\mathbf{p}_{Tc}, \mathbf{p}_{Oc})$ for channel $k = T, O$.[3] The profits of a firm f are the sum of (13) across all countries c, $\sum_c \pi_{cf}$. We write this here in two separate rows for the traditional channel ($k = T$) and the online channel ($k = O$):

$$
\begin{aligned}
\pi_f \;\; = \;\; & \sum_{c \in C} \sum_{j' \in \mathcal{F}_{fk'}} \left(p_{j'Tc} - mc_{j'Tc}\right) s_{c,j'Tc}(\mathbf{p}_{Tc}, \mathbf{p}_{Oc}) L_c \\
& + \sum_{c \in C} \sum_{j' \in \mathcal{F}_{fk'}} \left(p_{j'Oc} - mc_{j'Oc}\right) s_{c,j'Oc}(\mathbf{p}_{Tc}, \mathbf{p}_{Oc}) L_c.
\end{aligned}
$$

Because the demands $s_{c,jkc}(\mathbf{p}_{Tc}, \mathbf{p}_{Oc})$ depend only on the local prices in country c, the first-order conditions for profit maximizing prices can be solved as usual for each country separately.

Integrated markets After integration of the online distribution channel, consumers in each country c face an increased choice set because they can also purchase in other countries $d \neq c$, so the market shares $s_{c,jkd}$ will not necessarily be zero for $d \neq c$. To purchase these products abroad, consumers may face a shipping cost τ_{cd} to ship products from the country of purchase d to their own

[3] In (11), we simplified the market share notation to $s_{c,jk}$. But following Section 3, we now wrote this more explicitly as $s_{c,jk} = s_{c,jkc}$, because $s_{c,jkd} = 0$ for $d \neq c$ (i.e. under segmented markets consumers located in c only buy in c and not in any other country $d \neq c$).

country c (where we normalize $\tau_{cc} = 0$) The profit of a firm f after integration therefore becomes:

$$\begin{aligned}\pi_f =& \sum_{c \in C} \sum_{j' \in \mathcal{F}_{fT}} \left(p_{j'Tc} - mc_{j'Tc}\right) s_{c,j'Tc}(\mathbf{p}_{Tc}, \mathbf{p}_O + \tau) L_c \\ &+ \sum_{c \in C} \sum_{j' \in \mathcal{F}_{fO}} \sum_{d \in C} \left(p_{j'Od} - mc_{j'Od}\right) s_{c,j'Od}(\mathbf{p}_{Tc}, \mathbf{p}_O + \tau) L_c.\end{aligned} \tag{A.2}$$

where $\mathbf{p}_{Tc}$ is the domestic price vector of the traditional channel (as before), $\mathbf{p}_O$ is the price vector across all countries of the online channel, and τ is the shipping cost vector across all countries for online purchases (added to the online price).

The first term in A.2 captures the profits from selling in the traditional channel. This is the same as before: as this channel is still segmented, consumers do not buy in the traditional channel of other countries (i.e., $s_{c,jTd} = 0$ for $d \neq c$). But note that the domestic demand in the traditional channel now also depends on online prices in other countries (including shipping costs). The second term captures the profits from selling online. The demands by consumers in country c for online products in other countries $d \neq c$, $s_{c,jOd}$, may now be positive, and also depend on online prices in all countries. As a result, it is no longer possible to solve the first-order conditions for each country separately.

Firms choose prices to maximize total profits across countries (A.2), taking into account that consumers may consider to also buy products abroad. In the traditional channel T, each price p_{jTc} should satisfy the following necessary first-order condition (for each j and c):

$$\begin{aligned}\frac{\partial \pi_f}{\partial p_{jTc}} =& s_{c,jTc} L_c + \sum_{j' \in \mathcal{F}_{fT}} \left(p_{j'Tc} - mc_{j'Tc}\right) \frac{\partial s_{c,j'Tc}}{\partial p_{jTc}} L_c \\ &+ \sum_{d \in C} \sum_{j' \in \mathcal{F}_{fO}} \left(p_{j'Od} - mc_{j'Od}\right) \frac{\partial s_{c,j'Od}}{\partial p_{jTc}} L_c = 0.\end{aligned} \tag{A.3}$$

The first row of (A.3) captures the impact of an increase in the price p_{jTc} on profits in the traditional channel, which does not involve any other countries than c because demand in the traditional channel is segmented. The second row captures the impact of an increase in the price p_{jTc} on the online channel. This also involves other countries $d \neq c$, because consumers who substitute out of product j of the traditional channel may choose to buy online abroad.

In the online channel O, each price p_{jOc} should satisfy the following first-order condition (again, for each j and c):

$$\begin{aligned}\frac{\partial \pi_f}{\partial p_{jOc}} =& \sum_{c' \in C} \sum_{j' \in \mathcal{F}_{fT}} \left(p_{j'Tc'} - mc_{j'Tc'}\right) \frac{\partial s_{c',j'Tc'}}{\partial p_{jOc}} L_{c'} \\ &+ \sum_{c' \in C} \sum_{j' \in \mathcal{F}_{fO}} s_{c',j'Oc} L_{c'} + \sum_{c' \in C} \sum_{j' \in \mathcal{F}_{fO}} \sum_{d \in C} \left(p_{j'Od} - mc_{j'Od}\right) \frac{\partial s_{c',j'Od}}{\partial p_{jOc}} L_{c'} = 0.\end{aligned} \tag{A.4}$$

The second row of (A.4) captures the impact of an increase in the price p_{jOc} on profits in the online channel: this raises profits proportional to the demands from all countries (first term on second row), but it also reduces profits proportional to the online margins by affecting bilateral sales flows across all country pairs (second term on the second row). The first row captures the impact of p_{jOc} on profits in the traditional channel of all countries.

To write these first-order conditions in matrix form, we use the following notation. Let $q_{jkd} = \sum_c s_{c,jkd} L_c$ be the total demand for product j in channel k and country d. Furthermore, let $\mathbf{p}$, τ, $\mathbf{q}$ and $\mathbf{mc}$ be vectors with elements p_{jkd}, τ_{cd}, q_{jkd} and mc_{jkd}. Use $\mathbf{H}$ to denote the holding or ownership matrix across all alternatives (j, k and d), and use $\mathbf{\Omega}$ to denote the matrix with demand derivatives across all alternatives. In contrast to the case of segmented markets (where we had a matrix $\mathbf{\Omega_c}$ per country c), $\mathbf{\Omega}$ is now a matrix across all countries, and it includes non-zeros for products sold online in other countries. We can then write the first-order conditions (A.7) and (A.8) after integration as

$$\mathbf{p} = \mathbf{mc} - \left[\mathbf{H} \odot \mathbf{\Omega}\left(\mathbf{p}+\tau\right)\right]^{-1} \mathbf{q}\left(\mathbf{p}+\tau\right). \tag{A.5}$$

This system has the same form as in the standard case of segmented markets, where prices now include shipping costs for online products to consumers. To solve for the post-integration equilibrium, we iterate over firms' best response functions until a rest point of the system is reached. At each iteration consumers update their consideration sets (i.e. country of purchase for a product j).[4] To ensure convergence, we apply a damping factor to the markup term in (A.5).

We also considered an alternative possibility where shipping costs for online purchases are borne by the firms. In this case, the profit of a firm f after integration becomes:

$$\begin{aligned} \pi_f = & \sum_{c\in C} \sum_{j'\in\mathcal{F}_{fT}} \left(p_{j'Tc} - mc_{j'Tc}\right) s_{c,j'Tc}(\mathbf{p}_{Tc}, \mathbf{p}_O) L_c \\ & + \sum_{c\in C} \sum_{j'\in\mathcal{F}_{fO}} \sum_{d\in C} \left(p_{j'Od} - mc_{j'Od} - \tau_{cd}\right) s_{c,j'Od}(\mathbf{p}_{Tc}, \mathbf{p}_O) L_c. \end{aligned} \tag{A.6}$$

[4] More specifically, products j in the online channel $k = O$ are perfect substitutes across countries (because the idiosyncratic utility term $\varepsilon_{ic,j}$ in (4) does not contain a country of purchase dimension, as explained in section 3). Without shipping costs, we assign online demand for product j to the country with the highest utility. With shipping costs, online demand for product j may be positive in multiple countries, implying a complex combinatorial problem. We resolve this through a smoothing procedure (similar to our approach for estimating the demand model). We define a lower nest to each online product j that contains the different countries of purchase, and set a value of the nesting parameter close to one.

In the traditional channel T, each price p_{jTc} should satisfy (for each j and c):

$$\begin{aligned}\frac{\partial \pi_f}{\partial p_{jTc}} = s_{c,jTc}L_c + \sum_{j' \in \mathcal{F}_{fT}} \left(p_{j'Tc} - mc_{j'Tc}\right) \frac{\partial s_{c,j'Tc}}{\partial p_{jTc}} L_c \\ + \sum_{d \in C} \sum_{j' \in \mathcal{F}_{fO}} \left(p_{j'Od} - mc_{j'Od} - \tau_{cd}\right) \frac{\partial s_{c,j'Od}}{\partial p_{jTc}} L_c = 0.\end{aligned} \tag{A.7}$$

In the online channel O, each price p_{jOc} should satisfy (for each j and c):

$$\begin{aligned}\frac{\partial \pi_f}{\partial p_{jOc}} = \sum_{c' \in C} \sum_{j' \in \mathcal{F}_{fT}} \left(p_{j'Tc'} - mc_{j'Tc'}\right) \frac{\partial s_{c',j'Tc'}}{\partial p_{jOc}} L_{c'} \\ + \sum_{c' \in C} \sum_{j' \in \mathcal{F}_{fO}} s_{c',j'Oc} L_{c'} + \sum_{c' \in C} \sum_{j' \in \mathcal{F}_{fO}} \sum_{d \in C} \left(p_{j'Od} - mc_{j'Od} - \tau_{c'd}\right) \frac{\partial s_{c',j'Od}}{\partial p_{jOc}} L_{c'} = 0.\end{aligned} \tag{A.8}$$

We can write the first-order conditions (A.7) and (A.8) after integration in vector notation as

$$\begin{aligned}\mathbf{p} \;&=\; \mathbf{mc} - \left[\mathbf{H} \odot \mathbf{\Omega}\left(\mathbf{p}\right)\right]^{-1} \mathbf{q}\left(\mathbf{p}\right) \\ &\quad + \left[\mathbf{H} \odot \mathbf{\Omega}\left(\mathbf{p}\right)\right]^{-1} \left(\sum_{c \in C} \left(\mathbf{H} \odot \mathbf{\Omega}_c\left(\mathbf{p}\right)\right) \tau_c \right).\end{aligned}$$

The first row describes the pricing condition in the absence of shipping costs, showing a uniform markup term capturing consumer price sensitivities across countries. The second row takes into account the pass-through of shipping costs, which gives rise to non-uniform markups with a higher weight to consumer price sensitivities in domestic countries. Note that this condition yields uniform product-level prices in the online channel. In contrast, when consumers bear the shipping cost, product-level prices and total prices differ between countries.