Are Online Markets More Integrated than Traditional Markets? Evidence from Consumer Electronics *

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Abstract

Did the Internet make international markets more integrated? To address this question, we study long-term international price differences and their speed of convergence, based on a unique data base for identical goods sold in both online and traditional "brick-and-mortar" distribution channels, covering ten European countries. We find that long-term international price differences are closely comparable between both distribution channels. Furthermore, international price differences converge only slightly faster online than offline, and the differences in the international price differences between online and offline converge at a very fast rate. Finally, regardless of the distribution channel, long-term price differences are lower and converge faster within the same currency union. Our findings imply that online markets are currently not more integrated than traditional markets.

Key Words: *International price differences; international price convergence; difference-in-difference convergence; market integration; e-commerce*

JEL Classification: L13, L68, L86

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1 Introduction

The rapid development of the Internet has created new opportunities to make international markets more integrated. Just like within national markets, the Internet provides the potential of more consumer information, reduced search costs and increased shopping convenience across countries. On the supply side, online retailers have significantly improved their home delivery services, also across national borders. While policy makers have recognized that the Internet can improve market integration, they have also realized that this potential may have remained underexploited. This is best illustrated by the European Commission's strategy to achieve a Digital Single Market. This program does not only aim to promote e-commerce activities across Europe, but also to reduce artificial online cross-border trade restrictions introduced by national governments or private companies. As part of this program, in May 2015 the European Commission launched an e-commerce sector inquiry to understand the nature of possible online trade barriers.

In this paper we ask the question whether the Internet has made international markets more integrated. A natural way to shed light on this question is by studying to which extent the Law of One Price (LOP) holds between countries. For traditional, brick-and-mortar distribution channels there is a considerable amount of empirical evidence on long-term deviations from the LOP and on the speed of convergence after short-term fluctuations. The latter may be interpreted as an indication of the extent to which adjustment costs prevent consumers from exploiting cross-border short-term arbitrage opportunities.

For the online distribution channel, evidence on the LOP is much more limited. But a few recent studies suggest that online international price differences may be relatively small under certain circumstances (Cavallo, Neiman and Rigobon (2014)), or that convergence in response to short-term shocks may be fast (Gorodnichenko and Talavera (2017)). However, no work has provided a direct comparison of international price differences and convergence between goods that are sold both online and through the traditional brick-and-mortar channel.[1]

This paper aims to fill this gap. We make use of a unique and comprehensive data set of relatively easy-to-trade consumer electronics products: portable PCs, desktops, tablets and smartphones. The data set contains more than two million price observations across a broad set of retailers for products sold during January 2012 and March 2015 in ten European countries, some from the euro area and some from outside the euro area. For each product, we observe the average transaction price at the traditional and at the online distribution channel. This enables us to make a direct

[1] Cavallo (2017) compares online and offline prices for identical goods within countries for a sample of large multi-channel retailers, but does not study the implications for international price differences and convergence.

comparison between the two channels, both regarding the magnitude of long-term international price differences and the rate of convergence in response to short-term shocks. To accomplish this, we first estimate a standard convergence model for long-term international price differences, separately for products sold offline and online. We then extend it to a difference-in-differences convergence model, where we assess to which extent the long-term international price differences differ between the offline and online channel, and at which speed the short-term fluctuations around the long-term differences in differences adjust.

We obtain the following main findings. First, although long-term international price differences between countries are considerable, they are closely comparable between products sold offline and online. In other words, the differences in international price differences between online and offline are small. To the extent that local distribution costs do not vary much across countries, the international price differences in both the online and offline channel may be interpreted as stemming from markup differences, i.e. pricing-to-market. Second, convergence to long-term international price differences turns out to be very fast on both channels (with half-lives for the elimination of shocks of at most a few months). The speed of convergence is only slightly higher on the online than on the offline distribution channel. This indicates that cross-border arbitrage opportunities are not exploited more intensely in the online channel. Quite strikingly, the *differences* in the international price differences between the online and offline channels show an even higher rate of convergence (with half-lives often less than a month). Finally, regardless of the distribution channel, countries within a currency union tend to show lower long-term price differences and a faster rate of convergence than countries with different currencies (either with a pegged or a fluctuating currency relative to the Euro). These findings continue to hold for various robustness analyses that account for heterogeneous effects.

In sum, our findings indicate that the Internet does not necessarily make markets more integrated: long-term international price differences and the speed of adjustment are comparable online and offline. This relates to the literature on online prices and price dispersion within a country, see e.g. Brynjolfsson and Smith (2000), Ellison and Ellison (2005, 2009) and Gorodnichenko, Sheremirov and Talavera (2018). A broad message from this literature is that the frictions relating to search, menu and information costs in traditional markets are also present in online markets. Our paper shows that, in an international context, these frictions actually appear to be equally strong in online as in traditional markets. But some caution in interpretation is needed here because we do not observe pure online or offline products in our data. When firms sell their products on both channels and set prices jointly, they may keep online and offline prices together. A comparison of pure online with pure offline sellers of the same products may thus give further insights on whether frictions on both channels differ.[2]

This conclusion is also relevant to policy makers. The share of cross-border transactions made online within the European Union is still small.[3] The above-mentioned sector inquiry by the European Commission resulted in a detailed report (European Commission (2017)). The report expressed concerns that the expected gains from e-commerce did not easily materialize, and that many obstacles may lock online buyers and sellers within the boundaries of their countries. In particular, it showed concerns with two practices: geo-blocking, whereby companies may prevent consumers from purchasing goods on foreign websites; and geo-targeting, whereby companies may deliver content that differs by the physical location of website visitors (based on geo-location tools allowing websites to identify the physical location of their visitors). Several EU documents confirm the common incidence of these practices.[4] Together with the relatively small share of online cross-border transactions, this may help explain our findings that online markets are currently not more integrated than traditional markets, and motivates the recent measures taken to remove cross-border online trade restrictions.

Contribution to the literature Our paper contributes to a large body of literature on convergence to the Law of One Price (LOP) in traditional markets. Parsley and Wei (1996) and Fan and Wei (2006) studied convergence to the LOP between cities within a single country (U.S. and China, respectively). Price convergence between countries was first studied at the aggregate level by Frankel and Rose (1996) and Obstfeld and Rogoff (2000), among others. Subsequent studies reconsidered international price differences and the speed of convergence at the more disaggregate

[2]In Subsection 4.2, we provide a comparison between the 10% deciles with the highest and lowest offline share, and we do not find a systematic pattern of faster convergence for more online-oriented products. But it would be interesting to provide a comparison between pure online and offline products with retailer-level data in future research.

[3]For instance, in 2015 only 9 percent of EU retailers were engaged in selling online to other EU countries, and only 16 percent of all individuals in the EU aged 16-74 purchased goods and/or services through the Internet from sellers based in another EU country in the last 12 months (Eurostat (2015), ICT usage in households and individuals (isoc_i) and enterprises (isoc_e) statistics).

[4]According to the above mentioned EU e-commerce inquiry, 36% of retailers do not sell cross-border, 38% track customer locations to implement geo-blocking and 11% of retailers indicate that they are contractually required to implement geo-blocking. Furthermore, a mystery shopping survey carried out in 2015 on behalf of the European Commission (2016) shows that, on average, 63 percent of all attempts at online cross-border purchase are blocked by sellers at different stages of the online shopping process.

sectoral level (e.g. Imbs, Mumtaz, Ravn and Rey (2005) and Crucini and Shintani (2008)), or at the product or firm level (e.g. Goldberg and Verboven (2005) and Mejean and Schwellnus (2009)). In general, the studies that rely on disaggregate price data often document relatively large long-term deviations from the LOP, but a relatively fast rate of convergence to the long-term price differences (because they avoid "dynamic aggregation bias" as shown by Imbs, Mumtaz, Ravn and Rey (2005)). Some studies aim to uncover the sources of the price differences, i.e. local costs (non-tradables) or markups (pricing-to-market), relying either on direct cost information (e.g. Gopinath, Gourinchas, Hsieh and Li (2012)), pricing of bundled product features (Dvir and Strasser (2018)) or on structural models of oligopoly markup pricing and incomplete cost pass-through (Verboven (1996), Goldberg and Verboven (2001), Goldberg and Hellerstein (2007) and Nakamura and Zerom (2010)).

In recent years, a number of studies aimed to obtain new insights into the LOP by looking at prices of goods that are sold online. There are several reasons for this interest. The first reason is practical, as it is easier to collect data for online markets. Cavallo (2017) stresses this advantage and convincingly shows how online prices may provide a good proxy for offline prices. Second, online markets may provide a strong test case for the LOP, as local cost differences are likely to be small and arbitrage may be easier to implement for products sold online. Three papers have studied international price differences in online markets.

Boivin, Clark, and Vincent (2012) investigate the prices of three major online book sellers (Amazon, BN and Chapters) in the U.S. and Canada. They find considerable price differences, and attribute these to exchange rate fluctuations between both countries. More recently, Cavallo, Neiman and Rigobon (2014) collected a data set of more than 100,000 traded goods sold by the same four global retailers (Apple, H&M, Zara and IKEA) in a large number of countries. They also find that international price differences exist between countries with different currencies, but price differences turn out to be small between countries within the same currency union (the eurozone). Gorodnichenko and Talavera (2017) collected a similarly large data set with more than 100,000 goods (including software, electronics, tools, computer parts, and photo equipment), covering a large number of retailers. They compare the U.S. and Canada over a time span of almost five years. They find that prices in online markets show a faster rate of convergence than documented in earlier studies for traditional stores. In another paper, Gorodnichenko, Sheremirov and Talavera (2018) analyze a price setting mechanism in online markets using a dataset of daily U.S. and U.K.

price listings and the associated number of clicks for a broad coverage of goods from a major shopping platform. They document that although online prices change more frequently than offline prices, they exhibit similar imperfections including stickiness, low synchronization of changes, large cross-sectional dispersion, and low sensitivity to predictable fluctuations in demand.

We contribute to this interesting recent literature by providing a direct comparison between identical goods that are sold both online and through traditional brick-and-mortar channels. This approach provides interesting new insights. First, our finding that international price differences are equally large on the online and offline distribution channel may at first seem to contradict the finding of Cavallo, Neiman and Rigobon (2014), who establish very small price differences online. However, their results obtain only for countries within the same currency union (where we also find smaller price differences), and more importantly they apply in a setting where the products are sold by the same global retailers. Such global retailers may predominantly follow uniform pricing strategies (as recently documented by DellaVigna and Gentzkow (2017) within the US), whereas small retailers may still price to market. Our comprehensive sample with a broad coverage of retailers picks up this heterogeneity in pricing strategies.

Second, our finding that the speed of price convergence is comparable online and offline may seem to differ from the conclusion of Gorodnichenko and Talavera (2017). However, their study considers only online markets, and our estimates of the speed of convergence in online markets are, in fact, comparable to theirs (with half-lives less than a few months). Because we have price data for identical goods sold both online and offline, we can add the conclusion that the rates of convergence are (almost) equally fast on the offline distribution channel when identical products are directly compared across both retail channels. Furthermore, we show (through our difference-in-differences convergence model) that the two retail channels are very closely connected, and temporary differences in the price differences between the online and offline channel are often halved in less than a month. Compared with Gorodnichenko and Talavera (2017), our data on four categories of consumer electronics has relative advantages and disadvantages. The advantages are that: (i) we can make a direct comparison between identical goods sold online and offline; (ii) we observe a large number of countries; and (iii) we observe a large number of products with broad coverage in each country, and produced by the same global (Asian) manufacturers. There are two relative limitations: our focus on consumer electronics is less comprehensive; and we do not observe prices of the same products for multiple sellers within one country or across countries, which could yield additional insights. In future research, it would therefore be interesting to extend our approach to broader data sets, covering different product categories, countries and individual retailers.

The remainder of the paper is organized as follows. Section 2 discusses the data set. Section 3 presents the model and Section 4 discusses the empirical results. Finally, Section 5 concludes.

2 Data

We first describe the raw data and the construction of the final sample. Next, we discuss summary statistics and the scope of arbitrage opportunities. Finally, we discuss our procedure to aggregate the information on raw products to more aggregate products with a longer duration in the sample, although we also study the raw product information in a robustness analysis.

Raw data and construction of final sample We make use of a data set from GfK Retail and Technology, which is one of the largest market research firms globally, and covers a comprehensive and representative number of brick-and-mortar and online retailers selling consumer electronics. More specifically, we use monthly time series data between January 2012 and March 2015 on sales and average transaction prices for four consumer electronics product categories: mobile computers, desktops, tablets and smartphones, sold in ten EU Member States. The countries included are six Eurozone members: Belgium, France, Germany, Italy, Netherlands, Slovakia, Spain; and three countries with own currencies: Denmark, Poland and the UK. The sample is representative both for the smaller independent sellers as well as for the large chain-stores.[5] The database was purchased by the European Commission and provided to us for this research.

The sales and transaction price data are at the highly disaggregate level of product and retail channel. In each category, a unique product is identified by its name. In the case of mobile computers this is a combination of: (i) brand, such as Acer or Sony; (ii) series, such as Aspire or Travelmate in the case of Acer; and (iii) model, such as V5-511 or S7-391 in the case of Acer Aspire. For the other three categories, the products are similarly defined by brand, series and

[5]In particular, the data set covers all retailers and resellers in the following channels: 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.). Although we do not know the coverage by country, GfK declares that the average market coverage in the EU is 87%, and a minimum of 40% market coverage is met by far for each country and for each product group.

model name. In each country and month a product can be sold online and/or through a traditional offline retail channel.[6] Sales volumes and turnover per item (product and sales channel in a month and country) were gathered at the same time as the product specification information. The average transaction price of the item was calculated as turnover divided by sales volume. This is therefore not identical to posted prices, but we have verified that they closely match based on some external website information on prices.[7] Note finally that the sales variable in our data is defined as sales in the country where the product is sold rather than the country where it is shipped to. However, cross-border sales in consumer electronics markets were very limited, so that both are very similar.

The unit of observation in our data set is defined by the country, month, product and distribution channel (online/offline). The initial data set includes 2,072,041 observations, i.e. on average 2,656 products per country (10), month (39) and channel (2). The initial number of observations is 997,927 for mobile computers, 477,746 for desktops, 246,663 for tablets and 349,705 for smartphones. We removed products that do not have trade brands or are unbranded (as prices of these products cannot be compared across countries). Next, we aggregated products offered by the same manufacturer which have small differences in model names.[8] We also removed products with less than 36 observations (i.e. with very limited coverage across the 10 countries and 39 months). We excluded Slovakia, which is the smallest country in the sample in terms of population and sales because many products were not sold there at all. Finally, we kept only products which were sold both online and offline.

[6]GfK uses a "point of sales tracking" technology, which reports which products are sold, when, where and at what price, 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. GfK assures various data quality controls.

[7]We have verified this based on historical online posted prices. However, since the last period in our data, March 2015, most products were replaced by new ones and historical prices cannot be found easily. We were able to find historical online prices for Germany on the website geizhals.de, from which we collected price information for the top 40 products in four categories (10 per category) in March 2015. The historical prices on this website are the lowest among listed online sellers. They are highly correlated with our online prices at 0.96. Similar websites for other countries do not have historical prices going back to March 2015.

[8]This aggregation was done for only two categories, laptops and desktops, for which the GfK database provides extremely detailed names. For example, for the Fujitsu Esprimo model series, we observe C710 and C710 USFF, which we aggregate to C710; and for Fujitsu Esprimo we also observe C5731 ESTAR5, C5731 E-STAR5 and C5731 ESTAR, which we aggregate to C5731 ESTAR. In general, such name differences are either typos or small specification differences. We have done a robustness analysis without aggregating. This gives similar results (although it reduces the number of observations and overall sales coverage).

Descriptive statistics and scope of arbitrage opportunities The final sample includes the following data for 9 countries in two distribution channels (offline and online) between January 2012 and March 2015: (i) 242,368 observations for 2,034 unique portable computers with approximately 68.5 million total unit sales (85.6% of total unit sales of the original data); (ii) 115,708 observations for 1,106 unique desktops with approximately 21.2 million total unit sales (69%); (iii) 99,100 observations for 848 different tablets with approximately 83.5 million total unit sales (86.9%); (iv) 89,698 observations for 594 different smartphones with approximately 206 million total unit sales (59.2%).

Table 1 shows summary statistics for our individual product-level data in the top panel, and the scope of arbitrage opportunities in the bottom panel. Both panels show the information separately for each of the four product categories, and compare the online and offline sales channel. The summary statistics in the top panel show that portable computers and desktops are on average more expensive than tablets and smartphones. There is considerable price dispersion for all categories. This may to some extent be due to product quality differences reflected in the product characteristics, but it may also be due to variation across countries. Interestingly, with the exception of smartphones, the average price difference between identical products sold online or offline is negligible for all categories.[9] At the same time, there is quite some dispersion in the gap between online and offline prices. For example, portable PC products are on average €1.8 more expensive when sold offline instead of online, but 10% of the products is more expensive offline by at least €71.7, whereas 10% is less expensive offline by at least €69.0.

The second panel of Table 1 considers the size of the markets and compares the scope of arbitrage opportunities in the offline and online channel. Notice first that the majority of sales is still offline, but the importance of online sales is growing and reached 21% across all categories during the considered period. The next columns calculate the share of total sales that is sold at a premium price of at least 5%, 10% and 20% as compared to the cheapest country. For example, 48.5% of offline sales and 48.4% of online sales in the portable PC category can be purchased at least 10% more cheaply in another EU country, and 26.3% of both offline and online sales can be purchased at least 20% more cheaply in another country. Similar and often even higher numbers hold for the other categories. Interestingly, the measures for arbitrage opportunties are closely comparable for the online and ofline sales channel.

[9] Smartphones are an exception because of bundling practices with mobile tariff plans. We will come back to this later.

The last column explores this further by calculating the share of sales that can be purchased more cheaply abroad after accounting for shipping costs. To compute this, we use bilateral parcel shipping costs per kg from a study by Meschi, Irving and Gillespie (2013) conducted for the European Commission, and multiply this by the weight of each product. We find that, depending on the category, between 63% and 69% of the value of sales can be purchased more cheaply abroad, with very similar shares for online and offline.[10] In sum, both the offline and the online channel show a considerable scope of arbitrage opportunities, which are currently not exploited.

[10] Note that these shares are defined relative to total sales, which includes the sales of the cheapest country. Since this is often a large country (Germany or the UK), the shares would be even higher if we exclude the cheapest country itself.

Table 1: Summary statistics and arbitrage opportunities

		Summary statistics				
		Prices (€)				N
		Mean	SD	p10	p90	
Portable PCs	Offline	637.6	340.5	345.9	1118.0	121,184
	Online	635.8	343.8	338.5	1126.2	121,184
	Offline-online	1.8	93.2	-69.0	71.7	121,184
Desktops	Offline	689.2	474.9	351.0	1192.1	57,854
	Online	686.8	473.1	340.8	1199.0	57,854
	Offline-online	2.4	181.6	-102.6	96,7	57,854
Tablets	Offline	337.8	154.4	137.0	550.0	50,298
	Online	340.1	155.2	135.0	549.0	50,298
	Offline-online	-2.3	44.3	-37.0	30.0	50,298
Smartphones	Offline	260.2	188.4	60.0	564.0	44,849
	Online	292.2	197.6	80.7	600.0	44,849
	Offline-online	-32.0	88.6	-146.0	37.0	44,849

		Arbitrage opportunities					
		Sales	Revenues	Share of revenue with price difference:			
		(mln)	(mln €)	>5%	>10%	>20%	>shipping costs
Portable PCs	Offline	16.1	10076.2	63.1	48.5	26.3	62.7
	Online	5.0	3005.4	61.6	48.4	26.3	63.6
Desktops	Offline	5.3	3548.6	59.9	49.7	33.5	64.6
	Online	1.2	739.9	54.9	45.1	29.4	65.6
Tablets	Offline	17.7	5427.6	63.2	47.2	30.0	66.6
	Online	4.6	1439.2	60.3	41.7	19.5	67.6
Smartphones	Offline	52.5	9968.5	88.2	87.4	85.8	68.6
	Online	10.8	2544.9	84.8	83.3	81.0	69.6

Notes: Calculations are based on data set of consumer electronics products sold online and offline in nine countries between January 2012 and March 2015. The top panel shows summary statistics for prices (in Euro), where an observation refers to a country, month, individual product and distribution channel (online/offline). The bottom panel shows: total sales in annual terms (in million and million Euro); share of sales with a given percentage price difference compared to the cheapest country; and share of sales that can be purchased more cheaply in another country after accounting for shipping costs. The shares are relative to total sales, i.e. including the cheapest country.

Table 1 provided summary statistics and an overview of arbitrage opportunities at the level of the individual product and retail channel. It is also of interest to calculate average cross-country price differences with respect to a base country (Germany). We have computed these averages for our four product categories, and plotted them in Figure A.1 in Appendix A. Among other things, this shows that Belgium and Denmark are on average more expensive than Germany for all categories, whereas Poland is less expensive. It also shows that the cross-country price differences are comparable for the online and traditional channel. We will discuss this in more detail below, based on our convergence model from which we can estimate long-term price differences.

Aggregation As discussed above, the data set contains a very large number of products. For instance, Apple's iPhone 4S is sold in versions with different memory size of 8GB, 16GB, 32GB and 64GB. Moreover, products typically stay on the market for only a limited number of months and are replaced by newer related models. For instance, Apple launched its iPhone 4S in October 2011, and released the next version iPhone 5 less than a year later in September 2012. As a result, the average product lifetime within a country may often be relatively short, and not completely overlap with the lifetimes of the same products in other countries.

To have a sufficiently long time series across all countries, it will therefore be useful to compute sales-weighted average price indices at various aggregation levels. The weights are based on a product's total sales across all countries and the entire time period, so we use fixed baskets as weights. We consider three different aggregation levels. First, we aggregate to the level of the four broad product categories. Second, we aggregate to the level of the product category and brand, where we retain the three most important brands based on total sales and presence in all countries and a fourth group "other brands" of each category (e.g. Apple, Asus, Acer and other brands for portable computers). Third, we consider "aggregated" products, defined as top selling products that were sold under slightly different names at the same or at different periods in time. For instance, there are different model names for the Apple Macbook Air, and we group these together to construct a single price index for the Apple Macbook Air. To illustrate this further, Table A.1 in the Appendix shows for each product category examples of two aggregated products which we constructed. The extent of aggregation differs by category. In general, there are many models of mobile PCs and desktops that can be associated with the same series. On the other hand, there is typically a smaller range of models of tablets and smartphones that belong to the same series.

Each of the three aggregation levels has its relative advantages and disadvantages. The highest aggregation level (category) gives full coverage across all countries and the entire period. Furthermore, it provides a convenient way to summarize the results. However, this aggregation level ignores heterogeneity and may therefore underestimate the rate of convergence (as illustrated by the early country-level studies of price convergence, and referred to as dynamic aggregation bias by Imbs, Mumtaz, Ravn and Rey (2005)). The second aggregation level (category/brand) still gives full coverage across the panel and accounts for brand heterogeneity, but it is less convenient to present. Finally, the third and lowest aggregation level ("aggregated" products) accounts for product heterogeneity. However, it does not necessarily result in full coverage of the panel, so we will restrict attention to 36 top selling products that have good coverage over time and across countries.

We further explore the heterogeneity of sellers in several ways. First, for each category we divide brands into two groups depending on their size in terms of share in total sales over the whole period. For each group we compare price convergence of products that are sold both online and offline in the same period. Second, in the segment of smaller brands we create two groups, high versus low online sales, based on the share of sales which they make online over the whole period. For some sellers the online channel is more important than for others, so we can assess how this affects relative price strategies. Third, in each category we divide all products into two groups below and above the median price. In this way, we study whether there is a higher speed of convergence for products with higher prices due to more searches by consumers and arbitrage.

To construct the price indices, we take the set of individual products m for each considered aggregate product i, i.e. all $m \in S_i$. For each aggregate product i, we regress the price $r^k_{m,c,t}$ of individual product m and distribution channel k (online or offline) in country c at period t on a full set of individual product fixed effects δ_m and a set of 702 fixed effects $\theta^k_{i,c,t}$ for distribution channel, country and period ($2 \times 9 \times 39$). We take the following logarithmic regression:

$$\log r^k_{m,c,t} = \theta^k_{i,c,t} + \delta_m + \epsilon^k_{m,c,t}$$

We use weighted least squares, based on the total sales of a product m and channel k across all countries and periods to weigh the observations on the individual products. The price index of aggregate product i in country c relative to a base country B is then $q^k_{i,c,t} = \exp(\theta^k_{i,c,t} - \theta^k_{i,B,t})$. Note that a country c's absolute price index from the weighted least squares regression can be interpreted as a weighted geometric average (or Stone index), i.e. $\bar{q}^k_{i,c,t} = \exp(\theta^k_{i,c,t}) = \exp(\sum_{m \in i} w^k_m \log r^k_{m,c,t})$, with w^k_m as fixed sales weights (e.g. Moschini, 1995). In our analysis below, we will also report on a disaggregate approach with prices for individual products m, $r^k_{m,c,t}$, and alternative assumptions on how to cope with missing observations of individual products.

We perform these regressions for various aggregation levels i. First, we consider each of the four product categories (so i refers to laptops, tablets, smartphones and desktopics), and hence we obtain price indices at the level of the category. Next, we perform these regressions by category and brand to retrieve price indices at the level of the category and brand. Finally, we perform the regressions by aggregated product, and retrieve the price indices at this aggregate product level.[11]

Figure 1 shows the evolution of the constructed category-level price indices $q_{i,c,t}^k$ for each country relative to the base country, which we take to be Germany.[12] For each category, the left part shows the price evolution of the traditional channel, and the right part shows the evolution of the online channel. We can draw the following preliminary conclusions. First, price differences relative to Germany seem to be large and persistent. For example, for each category Denmark tends to be the most expensive throughout the entire period. Poland is often the least expensive (except for smartphones where the UK tends to be the cheapest). Second, the international price differences appear to be large and persistent for both the online and the traditional distribution channel, although there are also short-term fluctuations. There is no obvious indication that price differences are lower online.

3 Empirical framework

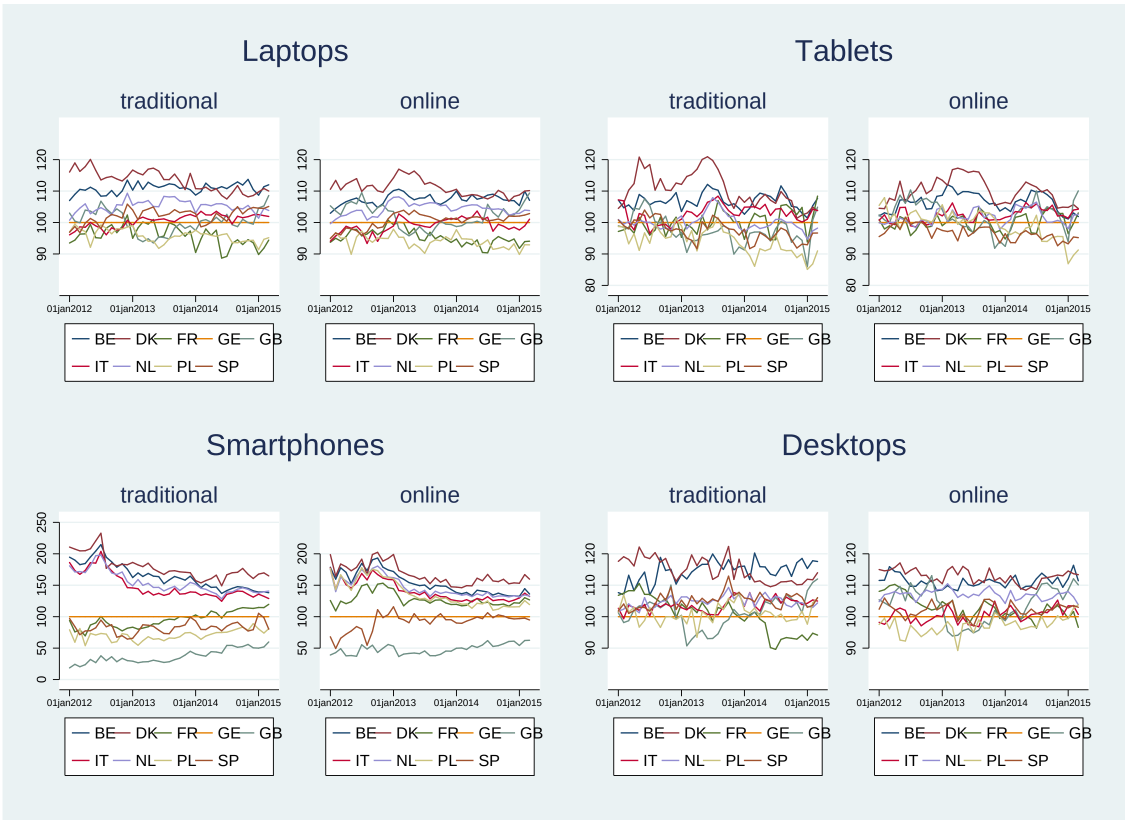
The literature on the LOP (reviewed in the introduction) has typically interpreted the presence of long-term price differences as evidence of unexploited arbitrage opportunities. Similarly, it has viewed estimates of the speed of convergence as evidence on the extent to which short-term arbitrage opportunities remain available to consumers. Such short-term arbitrage opportunities may arise because of product- and country-specific shocks that induce temporary deviations from the long-term price differences. These shocks may not only arise from exchange rate fluctuations (which are only relevant for the few non-Euro zone countries). They arise more broadly from both demand and supply side factors, for example relating to the presence and activities of local retailers. A high speed of adjustment may be due to low adjustment costs that induce retailers to re-set their prices quickly after being confronted with price changes abroad, or it may stem from direct arbitrage activities where consumers substitute to other retailers.

In this paper, we are correspondingly interested in modeling both the long-term international price differences and the speed at which short-term fluctuations converge to the long-term price differences. Furthermore, we also want to assess to which extent these long-term price differences

[11] At the category level, these regressions result in high R-squared values equal to 0.96 for desktops, 0.91 for laptops, 0.83 for tablets, and 0.57 for smartphones. They are comparably high at the category/brand level and tend to be lower at the aggregated product level.

[12] We use Germany as a base country because it is the largest country in population terms in the EU with the greatest total sales in our database. Using another country as a base does not change our results.

Figure 1: Evolution of international price differences



Notes: Each graph shows the evolution of the country-level price indices relative to Germany, by category and distribution channel. Based on flexible sales-weighted ordinary least squares regressions, as discussed in the main text.

are different between both distribution channels, online and offline. Throughout the discussion, a product i corresponds to one of the aggregation levels discussed in Section 2, i.e. category, brand or aggregated (top-selling) product, or alternative breakdowns of brands. The distribution channel k refers to either the online or the offline channel.

Convergence of international price differences For each distribution channel, we first consider a panel data regression to estimate the long-term international price differences, and the speed of convergence to these long-term differences in response to short-term fluctuations.

Define $p^k_{i,c,t}$ as the log-price difference of product i sold through distribution channel k in country c at period t, relative to a base country (Germany), i.e., $p^k_{i,c,t} = \log(q^k_{i,c,t})$, where $q_{i,c,t}$ refers to the relative price index defined above. For each product i and distribution channel k, we consider the following international price difference convergence regression:

$$\Delta p_{i,c,t}^{k} = \alpha_{i,c}^{k} + \beta_{i}^{k} p_{i,c,t-1}^{k} + \sum_{l=1}^{L} \gamma_{i,l}^{k} \Delta p_{i,c,t-l}^{k} + \varepsilon_{i,c,t}^{k}, \tag{1}$$

where $\Delta p_{i,c,t}^{k} \equiv p_{i,c,t}^{k} - p_{i,c,t-1}^{k}$ is the change in the international price difference, and $\Delta p_{i,c,t-l}^{k}$ are lagged changes, and L the number of lags included.

The parameter β_{i}^{k} denotes the speed at which international price differences for 'aggregate' product i and channel k converge to the long-term price differences in response to temporary shocks. Under the null hypothesis of no convergence, β is equal to zero and shocks to $p_{i,c,t}^{k}$ are permanent. There is convergence when β is negative between -1 and 0. The half-life of a shock is $\ln(2)/\ln(\beta_{i}^{k})$, i.e. the number of periods (months) it takes until half of a deviation from the long-term international price differences is eliminated. To test the hypothesis of no convergence, we apply the unit root tests of Levin-Lin-Chu (2002) and Pesaran (2007), which apply under alternative assumptions.

The parameter $\alpha_{i,c}^{k}$ is a fixed effect for product i, channel k and country c. It can be used to compute the long-term price differences for each product, channel and country (with respect to the base country Germany) as $\alpha_{i,c}^{k}/(-\beta_{i}^{k})$.

Convergence of differences in international price differences We next consider a panel data regression to estimate the *differences* in the long-term international price differences between online and offline, and the corresponding speed of convergence. Such a difference-in-differences convergence regression reveals the strength to which the online and offline distributional channels are connected.

Define $p_{i,c,t}$ as the log-difference in the international price difference between the online and offline distribution channel, i.e.

$$p_{i,c,t} = p_{i,c,t}^{online} - p_{i,c,t}^{offline}.$$

For each product i, we consider the following difference-in-differences convergence regression:

$$\Delta p_{i,c,t} = \alpha_{i,c} + \beta_{i} p_{i,c,t-1} + \sum_{l=1}^{L} \gamma_{i,l} \Delta p_{i,c,t-l} + \varepsilon_{i,c,t}. \tag{2}$$

As in the previous model, we are interested in both the speed of convergence β_i and the long-term differences in international price differences between online and offline, $\alpha_{i,c}/(-\beta_i)$.

4 Estimation results

We start our comparison between online and offline international price differences at the aggregate level of the category (Section 4.1). This is a convenient way to summarize the results, although it abstracts from richer forms of heterogeneity. We then consider additional results at the brand and segment level (Section 4.2) and at the product level (Section 4.3). Finally, we assess whether the results differ for countries with a common currency (the Euro) and countries that have different currencies (Section 4.4).

4.1 Category-level analysis

Table 2 shows the empirical results for convergence regression (1) at the level of the product category, for both the online and offline distribution channels. The estimates for the convergence coefficient β_i^k vary between -0.239 and -0.407 (excluding smartphones). The Levin-Lin-Chu tests reject the hypothesis of a unit root for all categories and for both distribution channels. Pesaran's CADF test points in the same direction but the power of the test appears to be diminished. This can be attributed to the high level of aggregation, as shown by Imbs, Mumtaz, Ravn and Rey (2005). Indeed, the power of the test is considerably greater in our more disaggregate brand-level analysis, as discussed further below. For smartphones, a unit root (lack of convergence) cannot be rejected. This may be due to the specific pricing policies for smartphones, which are often subject to varying handset subsidy practices by the local mobile operators, especially in the U.K. In our product-level analysis in Section 4.3 we will therefore remove the smartphone category. The estimated convergence coefficients imply fast convergence with a half-life of short-term shocks $(-\ln(2)/\ln(1+\beta^k))$ ranging between 1.3 and 2.5 months. For each category, the speed of convergence is comparable for the online and offline channel.

The country fixed effects $\alpha_{i,c}^k$ are usually highly significant, indicating persistent long-term price differences. Figure 2 shows the long-term price differences with respect to Germany (using $\alpha_c^k/(-\beta^k)$) for each country, each of the four product categories and both distribution channels. Overall, the long-term international price differences tend to be similar for the offline and online

Table 2: Convergence regressions: online versus offline

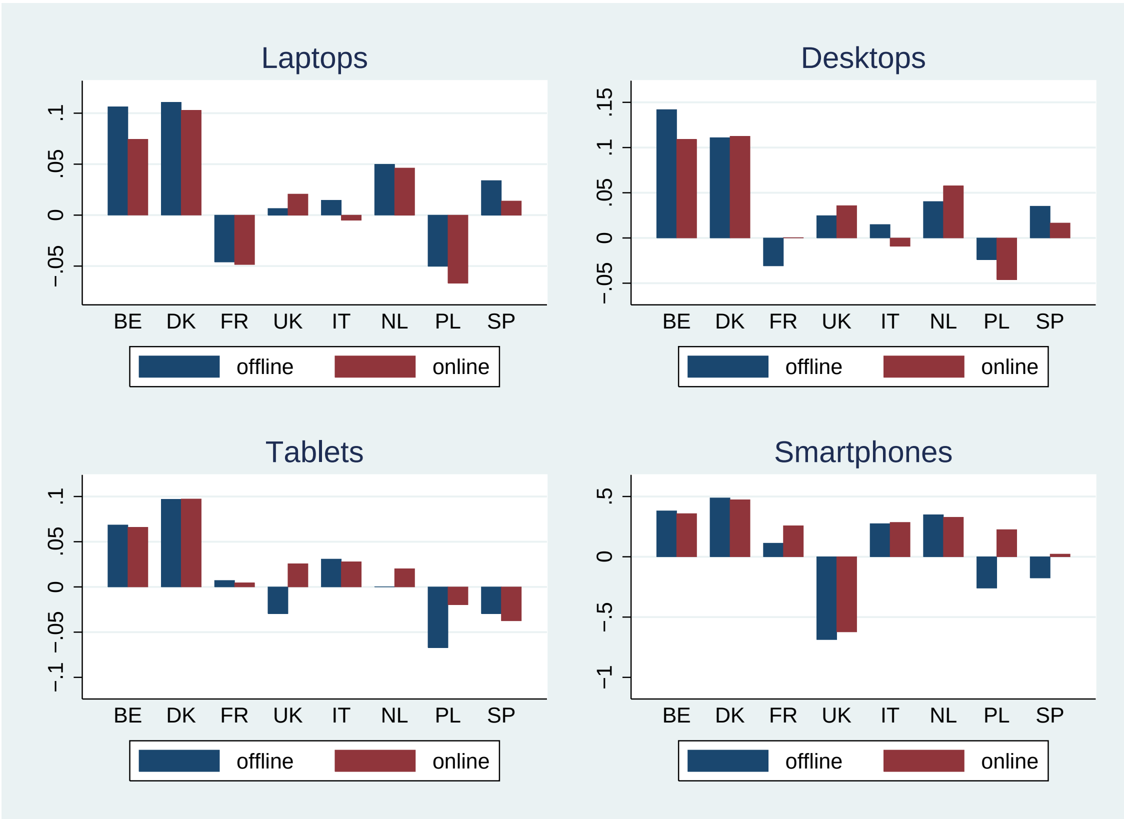
	Portable PCs		Desktops		Tablets		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.254	-0.239	-0.311	-0.278	-0.335	-0.407	-0.163	-0.125
	(0.050)	(0.057)	(0.063)	(0.059)	(0.064)	(0.065)	(0.040)	(0.035)
Belgium	0.019	0.025	0.034	0.039	0.022	0.028	0.058	0.047
	(0.005)	(0.007)	(0.008)	(0.009)	(0.006)	(0.007)	(0.021)	(0.021)
Denmark	0.026	0.026	0.035	0.031	0.033	0.039	0.077	0.061
	(0.006)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)	(0.024)	(0.024)
France	-0.012	-0.011	0.000	-0.009	0.001	0.003	0.042	0.014
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.016)	(0.013)
UK	0.005	0.002	0.011	0.007	0.009	-0.012	-0.101	-0.086
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.032)	(0.039)
Italy	-0.001	0.003	-0.003	0.004	0.009	0.013	0.046	0.034
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.018)	(0.019)
Netherlands	0.012	0.012	0.018	0.011	0.007	0.000	0.053	0.043
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.019)	(0.020)
Poland	-0.017	-0.012	-0.014	-0.007	-0.007	-0.027	0.037	-0.032
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.017)	(0.018)
Spain	0.004	0.008	0.005	0.010	-0.013	-0.012	0.004	-0.022
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.013)	(0.015)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.172	0.207	0.172	0.219	0.157	0.214	0.177	0.194
Pesaran's CADF	0.013	0.038	0.033	0.127	0.034	0.120	0.321	0.884
Levin-Lin-Chu p-value	0.0080	0.0002	0.0006	0.0000	0.0022	0.0036	0.0001	0.1947

Notes: Parameter estimates are based on convergence regression (1) at the category level.

channels. For example, Denmark and Belgium show considerably higher prices than Germany in the four product categories, and this is true for both offline and online. There are just a few exceptions with relatively large gaps between online and offline prices. For instance, tablets in the UK have lower offline prices and higher online prices than in Germany. The same is true for smartphones in Poland.

To shed further light on this, Table 3 shows the empirical results for the difference-in-differences convergence regression (2). Excluding smartphones, the estimates of β_i vary between -0.440 and -0.665, and the hypothesis of a unit root can be rejected. Interestingly, convergence towards the differences in international price differences between online and offline channel is thus even faster, with half-lives between 0.6 and 1.2 months. Furthermore, the small and often insignificant country fixed effects imply that these differences in the long-term international price differences are small or non-existing. In sum, the online and offline retail channels are strongly connected, showing small

Figure 2: Long-term price differences



Notes: Long-term price differences computed from $\alpha_c^k/(-\beta^k)$, based on the parameter estimates of convergence regression (1) shown in Table 2.

differences in the international price differences and a very fast rate of convergence.

These estimates allow us to conclude that the international price differences in online and offline markets (relative to Germany) tend to be much larger than the *differences* in these price differences. Figure 3 further supports this conclusion. The figure plots the long-term online prices differences on the horizontal axis against two variables on the vertical axis: the long-term offline price differences and the long-term differences in price differences (obtained from the estimates in Table 2 and Table 3). Figure 3 contains 30 observations: 8 country observations per category for tablets, laptops and desktops and 6 country observations for smartphones.[13] A simple OLS regression of the long-

[13]We dropped 2 observations for smartphones which were outliers with high long-term price differences, though they show an entirely consistent pattern.

Table 3: Convergence regressions: difference online - offline

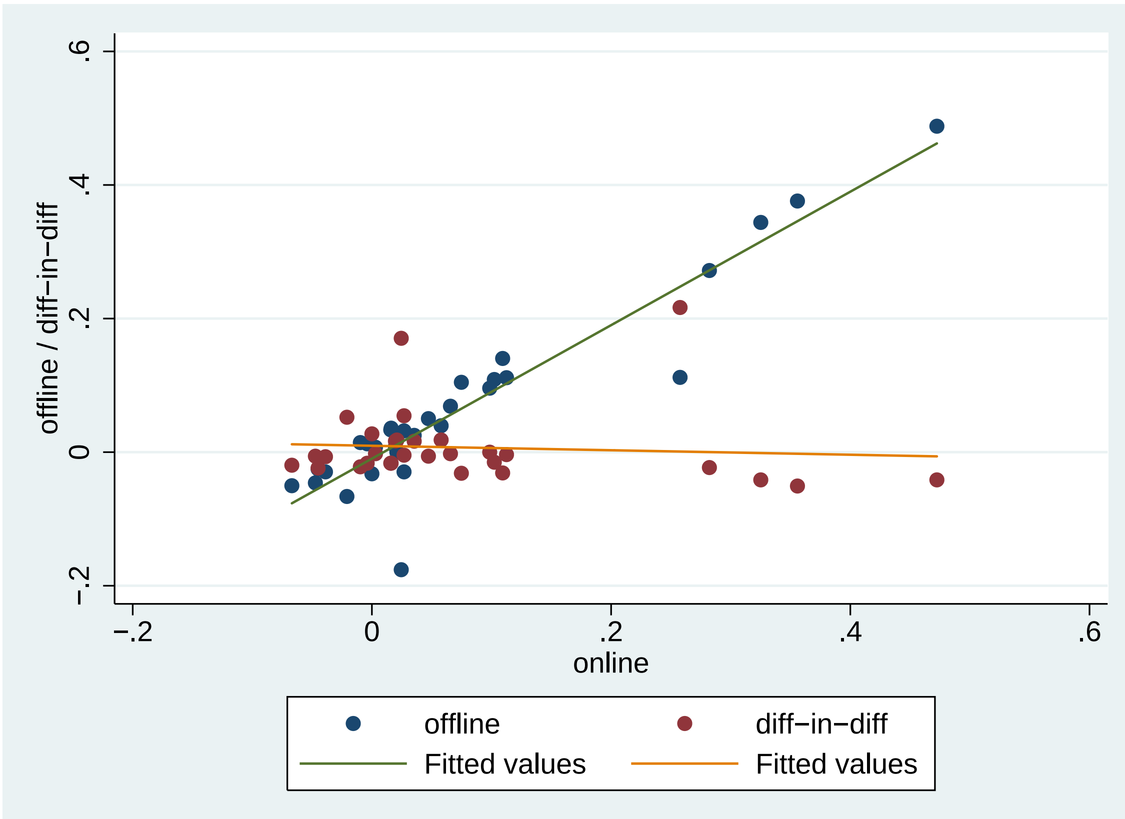
	Portable PCs	Desktops	Tablets	Smartphones
Lagged price	-0.665	-0.547	-0.440	-0.217
	(0.086)	(0.078)	(0.066)	(0.044)
Belgium	-0.021	-0.017	-0.001	-0.011
	(0.004)	(0.004)	(0.004)	(0.016)
Denmark	-0.010	-0.002	0.000	-0.009
	(0.003)	(0.004)	(0.004)	(0.016)
France	-0.004	0.015	-0.001	0.047
	(0.003)	(0.004)	(0.004)	(0.020)
UK	0.011	0.009	0.024	0.043
	(0.003)	(0.004)	(0.005)	(0.020)
Italy	-0.011	-0.012	-0.002	-0.005
	(0.003)	(0.004)	(0.004)	(0.016)
Netherlands	-0.004	0.010	0.008	-0.009
	(0.003)	(0.004)	(0.004)	(0.016)
Poland	-0.013	-0.013	0.023	0.120
	(0.003)	(0.004)	(0.005)	(0.033)
Spain	-0.011	-0.009	-0.003	0.037
	(0.003)	(0.004)	(0.004)	(0.016)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280
R-squared	0.221	0.321	0.326	0.178
Pesaran's CADF	0.004	0.085	0.000	0.544
Levin-Lin-Chu p-value	0.0001	0.0000	0.0000	0.1899

Notes: Parameter estimates are based on convergence regression (2) at the category level.

term offline price differences on the online price differences yields a slope of 0.99. Furthermore, a regression of the long-term diff-in-diffs on the online price differences yields a slope of -0.03. Thus, the long-term international price differences tend to be similar on average for the offline and online channels.

Our finding that long-term international price differences are closely comparable for the offline and online channel may shed some indirect light on the underlying sources. To the extent that cross-country differences in local distribution costs are limited in the online channel, the price differences would be attributable to markup differences, i.e., pricing-to-market. The relatively concentrated nature of the industries makes this a possibility. For example, in March 2015 the Herfindahl-Hirschman Index (HHI) in the offline (online) channel amounted to 1463 (1504) for laptops, 1962 (2023) for tablets, 1582 (1162) for desktops and 2016 (1739) for smartphones. Each category contains a few strong players, who may exercise their market power by pricing-to-market.

Figure 3: Long-term price differences



Notes: Based on 30 observations on long-term price differences for tablets, laptops, desktops and smartphones from Figure 2 and long-term diff-in-diffs implied by the regressions in Table 3.

A more complete understanding of the sources of the long-term price differences either requires direct cost information (as in e.g. Gopinath, Gourinchas, Hsieh and Li (2012)) or a structural oligopoly model to estimate markups. In a recent paper (Duch-Brown, Grzybowski, Romahn and Verboven, 2020), we conducted the latter approach for laptops, and find lower price sensitivities and higher markups in the higher income countries, which is consistent with pricing-to-market.

Our convergence regression models (1) and (2) were estimated after aggregating product prices to the category level in a first stage, based on the procedure outlined in Section 2. As a robustness analysis, we have also estimated both models at the individual product level in a single stage for each category, with country fixed effects and a full set of product fixed effects. The estimation results are shown in Tables B.1 and B.2 in Appendix B. These regressions involve a substantial loss of product data for the following reasons. First, when computing the log price differences for each product in each month relative to Germany, we lose observations on all products which were not sold in Germany. Second, we lose observations for products with a short period of observations or with gaps over time, because the model includes lagged values in the regressions. Nevertheless, the long-term price differences across countries, shown in Figure B.1 in Appendix B, are comparable to what we obtained through our two-stage procedure.[14] We will therefore proceed with two-stage regressions in our subsequent extensions that allow for more heterogeneity, as discussed in Section 4.2 and 4.3.

4.2 Heterogeneity: brand- and segment-level analysis

We begin by repeating the analysis for the most important brands in each category, i.e. the three most popular brands and the remaining other brands. In the Appendix, Table A.3 up to Table A.6 show the results parallel to Table 2; and Table A.7 up to Table A.10 show the results parallel to Table 3. The Pesaran's CADF unit root tests again reject the hypothesis of a unit root. As mentioned above, this indicates that the power of the test becomes greater at the brand-level. In terms of economic substance, the brand-level estimates confirm our above conclusions. First, long-term international price differences tend to be large and persistent, but they are closely comparable for the online and offline distribution channels. Second, convergence to these long-term differences is fast, especially for differences in the international price differences between online and offline.

To obtain further insights on the role of heterogeneity, we also consider different segments of main brands. We first group together the top six brands in each category, based on the total unit sales in the whole period. As shown in Table C.1, the top six laptop brands had a joint market share of 77.9%, of which 23.0% was sold online (with large differences across brands). The top six desktop brands had a joint market share of 81.3%, of which 15.7% were sold online. The top six tablet brands had a joint market share of 74.4% with about 20.1% sold online. Finally, the top six smartphone brands had a joint market share of 87.9%, with 16.9% sold online.

We divide each product category into two groups. The first group, 'large brands', includes the six main brands, with the exception of smartphones where the first group includes the four main

[14] To further explore this, we also performed regressions at the individual product level where: (i) we fill missing observations by either the average price of the product per country and distribution channel, or by the price in the previous period; and (ii) we reduce the number of lag differences to two periods. These extensions also give comparable results.

brands (as these already attain a comparable market share as the six main brands in the other categories). The second group, 'small brands', includes all other smaller brands in our data set. We estimate the model for each group to analyze whether there are differences in convergence between the large and small brands. Next, we divide 'small brands' into two groups. The first group, called 'small online share', contains brands with an online share of at most 25%. The remaining brands fall into the second group called 'large online share'. We use this threshold for desktops and smartphones. For tablets and laptops we use thresholds of 20% and 22% respectively, to ensure there is a sufficient number of observations in each group.

Tables 4 and 5 show the estimated convergence coefficients (first four rows). The detailed estimation results are shown in Appendix C. We find that the speed of convergence is usually comparable for the online and offline distribution channel for the various groups of products (with some exceptions).[15] The prices of products which belong to 'large brands' do not converge faster than those from 'small brands', except for smartphones. The prices of products belonging to 'small brands' with a large share of online sales converge faster than those with a 'small online share' in the case of desktops, but the opposite is true for laptops and smartphones. The diff-in-diff regressions in Table 5 do not show a systematic pattern across all product categories. But the convergence speeds are again higher for these differences in international price differences (as compared with the simple differences in Table 4), as found earlier when we did not consider heterogeneity.

Finally, we divide all products into a 'low-priced' and a 'high-priced' group, based on whether the price is below and above the median. The idea behind this is that there may be faster convergence for more expensive products due to more searches by consumers and arbitrage across borders. We do not however find systematic evidence for this. For desktops and smartphones, the prices for high-priced products converge faster than those for low-priced products. But a different pattern obtains for laptops and tablets.

In sum, the broad conclusions continue to hold when we allow for heterogeneity. But there do not seem to be strong systematic patterns that distinguish the different market segments, so we cannot draw clear conclusions on this basis.

[15] We also estimated single stage regressions at the individual product level (analogous to Table B.1), to attempt to distinguish between products that are either sold online or offline. However, we do not observe pure offline-only and online-only products, so we distinguish between the 10% deciles with the highest share of offline and highest share of online. We do not find a systematic pattern that would indicate a faster convergence for more online-oriented products. It would be interesting to explore this further based on retail-level data.

Table 4: Convergence coefficients: online versus offline

	Tablets		Desktops		Laptops		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Small online share	-0.405	-0.335	-0.307	-0.152	-0.506	-0.502	-0.347	-0.202
	(0.070)	(0.061)	(0.069)	(0.050)	(0.092)	(0.084)	(0.065)	(0.039)
Large online share	-0.418	-0.383	-0.357	-0.370	-0.167	-0.205	-0.136	-0.164
	(0.067)	(0.074)	(0.067)	(0.065)	(0.058)	(0.056)	(0.052)	(0.045)
Small	-0.312	-0.293	-0.305	-0.274	-0.259	-0.258	-0.188	-0.123
	(0.063)	(0.063)	(0.070)	(0.054)	(0.066)	(0.064)	(0.046)	(0.033)
Large	-0.241	-0.267	-0.295	-0.246	-0.264	-0.233	-0.318	-0.260
	(0.055)	(0.059)	(0.072)	(0.061)	(0.050)	(0.057)	(0.045)	(0.048)
Low-priced	-0.374	-0.311	-0.282	-0.286	-0.315	-0.315	-0.217	-0.138
	(0.066)	(0.061)	(0.060)	(0.055)	(0.056)	(0.064)	(0.045)	(0.034)
High-priced	-0.328	-0.390	-0.388	-0.367	-0.255	-0.187	-0.262	-0.209
	(0.057)	(0.064)	(0.071)	(0.072)	(0.054)	(0.056)	(0.053)	(0.050)

Notes: Parameter estimates are based on convergence regression (2).

4.3 Heterogeneity: product-level analysis

We now turn to an analysis of long-term price differences and the speed of convergence at the level of individual products. We assess the distribution across all categories, but we remove smartphones because in this category the price differences are heavily influenced by the common practice of handset subsidies by the local mobile operators. As discussed in Section 2, we construct a selection of top selling aggregated products which consist of related models that were sold in the same or different months. Table A.2 of the Appendix lists our set of aggregated products for each category. We retain a total of 36 products for mobile PCs, desktops and tablets sold both online and offline with a good coverage across the 9 countries and in the considered period.

Figure 4 shows the distribution of the convergence parameters for the online and offline channel (β_i^k, top part) and for the difference between online and offline (β_i, bottom part). This confirms the high convergence speeds found earlier at the more aggregate level, and in addition shows that there is heterogeneity in the convergence speeds across products. Furthermore, convergence speeds are higher for the differences in international price differences between online and offline (bottom part).

We next consider the distribution of the long-term price differences across products by computing the long-term absolute price differences by product and channel for every possible country pair (while in the above more aggregate analysis we considered price differences relative to Germany). Figure 5 shows that the distribution of the long-term international price differences is comparable

Table 5: Convergence coefficients: difference online - offline

Online-offline	Tablets	Desktops	Laptops	Smartphones
Small online share	-0.628	-0.496	-0.573	-0.519
	(0.088)	(0.071)	(0.092)	(0.060)
Large online share	-0.401	-0.643	-0.523	-0.217
	(0.070)	(0.085)	(0.076)	(0.055)
Small	-0.376	-0.605	-0.634	-0.255
	(0.067)	(0.074)	(0.080)	(0.046)
Large	-0.374	-0.479	-0.501	-0.301
	(0.064)	(0.071)	(0.080)	(0.040)
Low-priced	-0.386	-0.412	-0.621	-0.249
	(0.062)	(0.066)	(0.082)	(0.035)
High-priced	-0.424	-0.583	-0.542	-0.263
	(0.064)	(0.081)	(0.076)	(0.050)

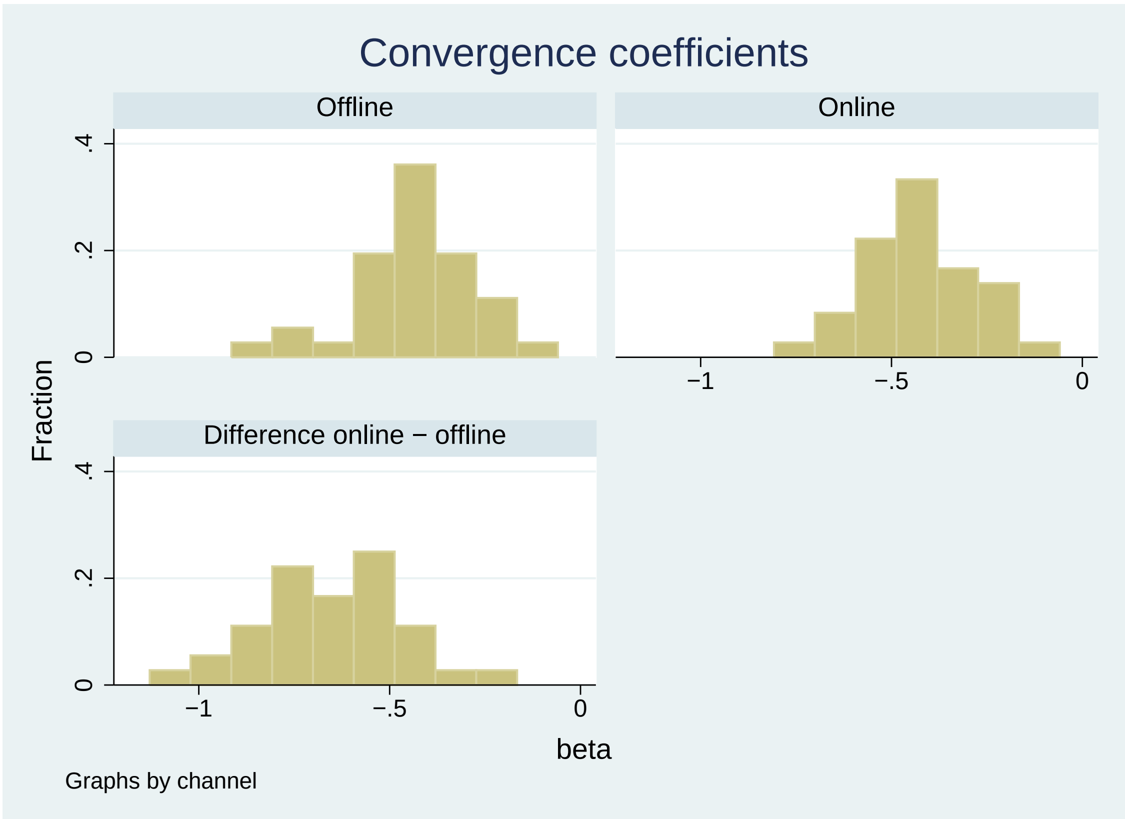
Notes: Parameter estimates are based on convergence regression (2).

for the online and offline channel (two charts in the top panel). Furthermore, the distribution for the differences in long-term price differences between online and offline is much more dense around zero, which confirms our earlier conclusion that online and offline prices are close to each other in the long-term.[16]

To assess the determinants of these long-term price differences, we estimated gravity regressions for the absolute bilateral price differences of every country pair and product (with 36 country pairs and 36 products this amounts to regressions with 1296 observations). Table 6 shows that distance (between the capital city of each country) and common border do not explain the absolute bilateral price differences. Country effects explain part of the variation. Bilateral price differences tend to be the lowest when the Netherlands, France or Germany are involved. Conversely, they are the highest when Denmark, Poland or the U.K. are involved. It is perhaps no coincidence that these are countries that do not share a common currency. We will address this in more detail in the next subsection 4.4.

[16] The price indices may be more volatile at the aggregate product level than at the category or categoy/brand level because the number of individual products used to construct the aggregate product price indices is smaller. Moreover, due to the high churning rate of consumer electronic products, the time dimension for many products is relatively short. This may influence persistent price discrepancies. For instance, it may be the case that the speed of price convergence is relatively high within a particular vintage of iPhone, but Apple may be able to maintain relatively large price discrepancies by launching new products.

Figure 4: Speed of convergence by product



Notes: The graph plots the estimated convergence coefficients by product, based on convergence regression (1) at the product level.

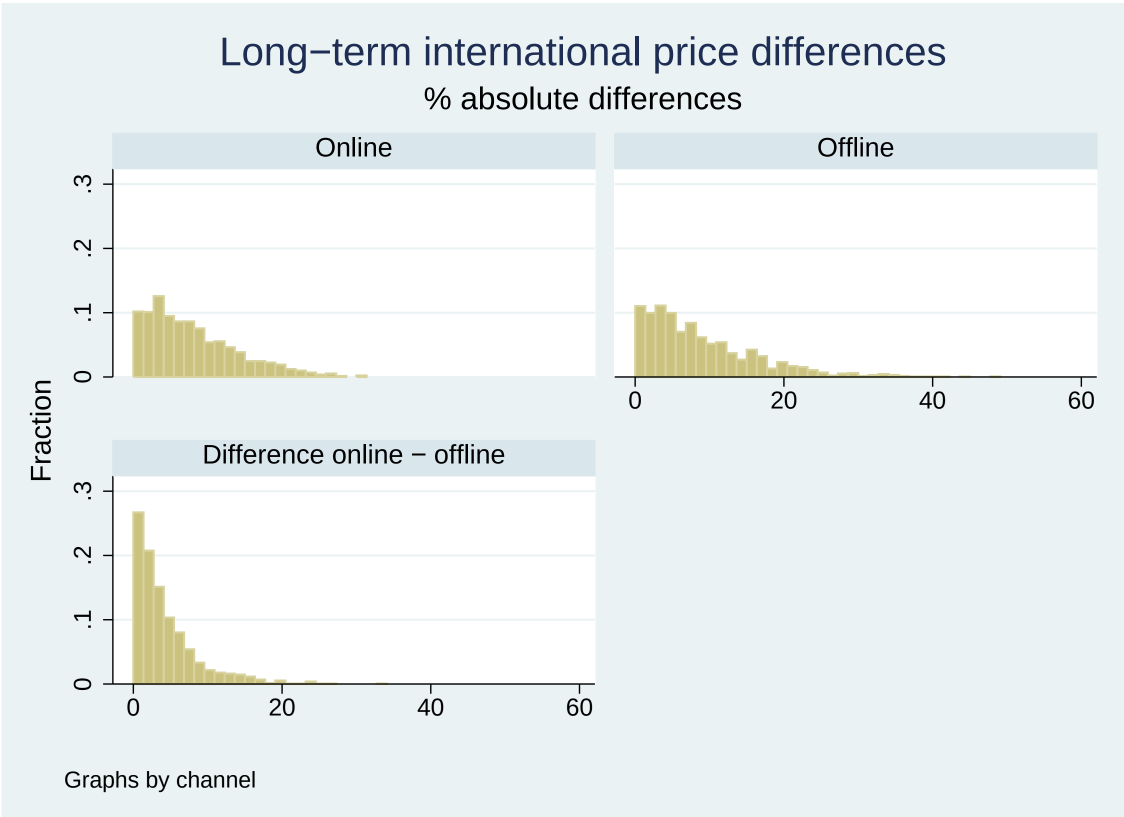
4.4 Common versus non-common currency

Table 7 summarizes the distribution of the convergence coefficients and the long-term bilateral price differences for the product-level analysis. The top panel considers all countries, the middle panel contains countries in the Eurozone (Belgium, France, Germany, Italy, the Netherlands and Spain) and the bottom panel considers the countries with different currencies (Denmark, Poland, the U.K. and again Germany).[17]

Table 7 confirms that international price convergence is fast for both the online and the offline channel, and even faster for the difference between the online and offline channel. Furthermore,

[17]To obtain the underlying parameters, we estimated the convergence models for the entire set of countries (as in the previous section), and then separately for the two subsets of countries (Eurozone versus different currency group).

Figure 5: Long-term international price differences across products



Notes: The graph plots the long-term international price differences by product and country pair, based on convergence regression (1) at the product level.

convergence appears to be on average faster within the Eurozone than between countries with different currencies.[18]

Table 7 also shows that long-term absolute bilateral price differences are on average relatively high for both distribution channels, and in fact only slightly lower online than offline (8.0% and 8.9%, respectively). The differences in these international price differences between online and offline are considerably smaller (4.2%). This is to be expected when the bilateral price differences on the online and offline distribution channel are positively correlated. Furthermore, the bilateral

[18]To further explore this, we also estimated convergence regressions at the category-level, again separately for Eurozone countries and countries with different currencies. The results, parallel to Table 2 in subsection 4.1, are displayed in Table A.11 and Table A.12 of the Appendix, and confirm that convergence is indeed significantly faster within the Eurozone.

Table 6: Determinants of long-term price differences

	Online	Offline	Difference
Distance	0.0026	-0.0000	-0.0019
	(0.006)	(0.007)	(0.004)
Common border	0.0029	0.0038	0.0008
	(0.006)	(0.007)	(0.004)
Belgium	0.0282	0.0530	0.0304
	(0.018)	(0.023)	(0.013)
Denmark	0.0508	0.0595	0.0200
	(0.020)	(0.025)	(0.014)
France	0.0248	0.0366	0.0259
	(0.020)	(0.024)	(0.014)
Great Britain	0.0283	0.0465	0.0395
	(0.019)	(0.023)	(0.013)
Germany	0.0242	0.0319	0.0206
	(0.020)	(0.025)	(0.014)
Italy	0.0267	0.0347	0.0272
	(0.022)	(0.028)	(0.016)
Netherlands	0.0183	0.0272	0.0202
	(0.018)	(0.022)	(0.013)
Poland	0.0439	0.0655	0.0387
	(0.021)	(0.026)	(0.015)
Spain	0.0293	0.0406	0.0262
	(0.023)	(0.029)	(0.017)
Observations	1,296	1,296	1,296
R-squared	0.653	0.603	0.518

Notes: Parameter estimates are based on regression of long-term price differences by product and country pair on distance, common border and country fixed effects.

price differences are on average lower within the Eurozone (7.3% for online and 8.1% for offline) than between countries with different currencies (9.9% for online and 10.6% for offline). The standard deviation of the bilateral price differences is also lower within the Eurozone.

In sum, we can conclude that international price differences are on average only slightly lower on the online than on the offline distribution channel. The international price differences are much lower and converge much faster within the Eurozone than between countries with different currencies.

5 Conclusions

We have studied international price differences and price convergence based on a unique data base with prices of identical goods sold both online and offline. We obtained the following main

Table 7: Long-term bilateral price differences and convergence coefficients

		Convergence coefficients			Price differences		
		Online	Offline	Difference	Online	Offline	Difference
All countries							
	Observations	36	36	36	1.296	1.296	1.296
	Mean	-0.428	-0.434	-0.651	8.0%	8.9%	4.2%
	St. Dev.	0.153	0.161	0.183	6.0%	7.5%	4.3%
	10th Pctile	-0.607	-0.614	-0.886	1.3%	1.3%	0.5%
	90th Pctile	-0.212	-0.189	-0.430	17.0%	19.5%	9.8%
	Min	-0.801	-0.867	-1.129	0.0%	0.0%	0.0%
	Max	-0.059	-0.160	-0.261	30.8%	47.7%	33.5%
Euro countries							
	Observations	36	36	36	540	540	540
	Mean	-0.477	-0.455	-0.641	7.3%	8.1%	3.7%
	St. Dev.	0.229	0.219	0.204	5.7%	7.5%	3.8%
	10th Pctile	-0.703	-0.744	-0.966	1.1%	1.3%	0.4%
	90th Pctile	-0.202	-0.201	-0.351	14.5%	16.5%	9.1%
	Min	-1.219	-1.100	-1.153	0.0%	0.1%	0.0%
	Max	-0.052	-0.113	-0.280	32.4%	57.4%	24.1%
Non-Euro countries							
	Observations	36	36	36	216	216	216
	Mean	-0.397	-0.457	-0.684	9.9%	10.6%	4.4%
	St. Dev.	0.187	0.221	0.267	6.9%	8.0%	4.5%
	10th Pctile	-0.706	-0.783	-0.993	2.3%	2.1%	0.6%
	90th Pctile	-0.156	-0.205	-0.357	19.8%	21.8%	10.7%
	Min	-0.789	-0.991	-1.264	0.0%	0.0%	0.0%
	Max	-0.052	-0.120	-0.119	28.6%	37.2%	26.4%

Notes: The left part shows summary statistics for the estimated convergence coefficients by product. The right part shows summary statistics for the estimated long-term price differences by product and country pair. Based on convergence regression (1) at the product level.

findings. First, long-term international price differences are closely comparable between both retail channels. Furthermore, the speed of international price convergence is only slightly higher online, and differences in the international price differences between the online and offline channel converge at a very fast rate. Finally, regardless of the distribution channel, countries within the same currency union show lower long-term price differences and a faster rate of convergence.

Our findings imply that online markets are currently not more integrated than traditional markets. From a policy perspective, this suggests that progress towards European market integration may require a close monitoring of the recent policies that aim to reduce online trade barriers, such as the geo-blocking and geo-targeting practices of manufacturers and retailers.

A unique feature of our data was the broad coverage of retailers within each of a large set of countries. We focused on four categories of tradable consumer electronics. In future research, it would be interesting to extend this analysis to other tradable product categories. Furthermore, our analysis compared online and offline prices for identical products at the level of the manufacturer. It would also be interesting to investigate what can be learned from such a comparison at the level of individual retailers.

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Appendix A

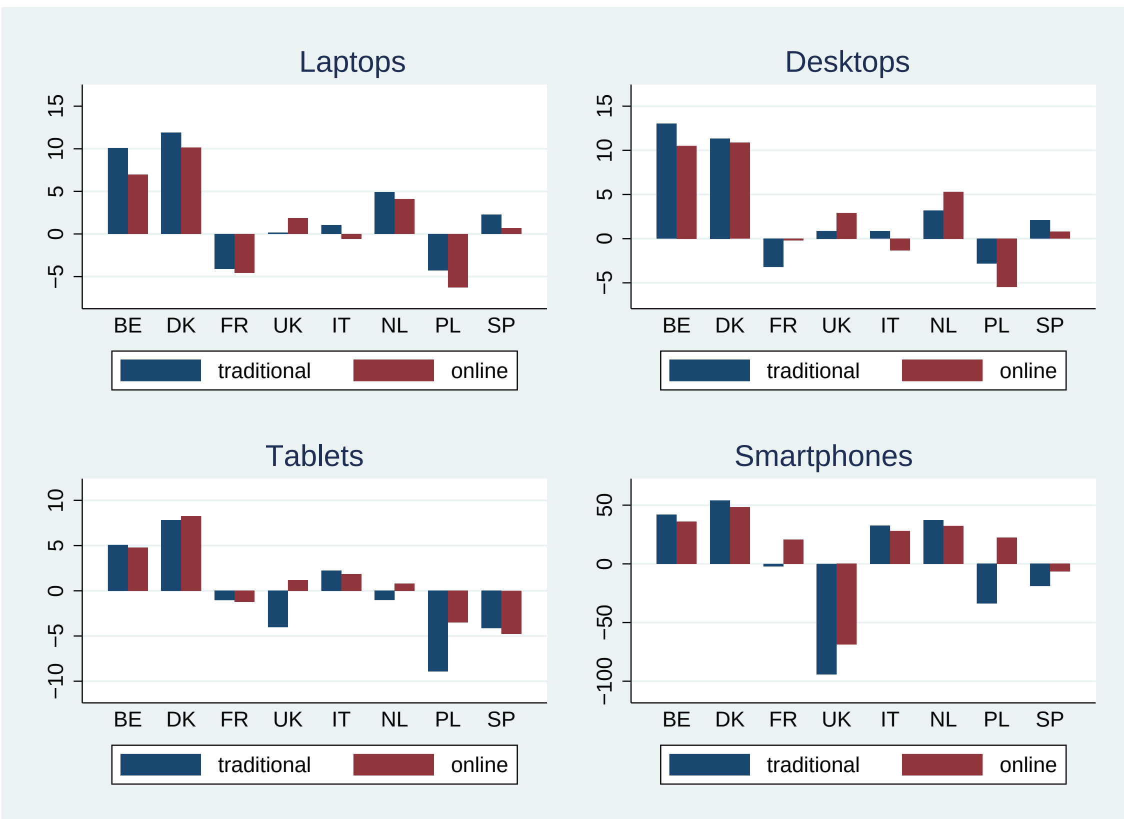
Table A.1: Examples of aggregated products by category

Portable PCs		Desktops		Tablets		Smartphones	
Apple Mac Air	Acer Aspire E	Acer Veriton	Apple Mac Mini	Acer Iconia A	Apple Ipad Air	Apple iPhone 4S	Samsung Galaxy Ace
11	E1	E430	MC815	A1-840 FHD 16GB	2 WiFi+CEL 128GB	8GB	2 I8160
13	E1-430	E430G	MC816	A3-A10 16GB	2 WiFi+CEL 16GB	16GB	2 I8160 NFC
MC504	E1-470	L4610G	MD387	A3-A10 32GB	2 WiFi+CEL 64GB	32GB	3 S7275 NFC LTE
MC506	E1-510	L4620G	MD388	A3-A10 WiFi 32GB	2 WiFi 128GB	64GB	4 G357F NFC LTE
MC965	E1-521	L4630G	MD389	Tab A1-810 16GB	2 WiFi 16GB		Duos S6802
MC966	E1-522	L6610G	MGEM2	Tab A1-810 8GB	2 WiFi 64GB		Plus S7500
MC968	E1-530	M2110G	MGEN2	Tab A1-811 WiFi+3G 16GB	WiFi+4G LTE 128GB		S5830
MC969	E1-531	M2610G	MGEQ2	Tab A1-811 WiFi+3G 8GB	WiFi+4G LTE 16GB		S5830I
MD223	E1-532	M2611G	SERVER MC936	Tab A3-A20	WiFi+4G LTE 32GB		Style G310 NFC
MD224	E1-570	M2631	SERVER MD389	Tab A3-A20 16GB	WiFi+4G LTE 64GB		VE S5839I
MD231	E1-571	M275	SERVER Z0	Tab B1-A71 16GB	WiFi 128GB		
MD232	E1-572	M290	Z0M9		WiFi 16GB		
MD711	E1-731	M4610G	Z0NP		WiFi 32GB		
MD712	E1-771	M4620G	Z0NQ		WiFi 64GB		
MD760	E1-772	M4630G					
MD761	E3	M6610G					
Z0M	E3-111	M6620G					
Z0NB	E3-112	M6630G					
Z0NC	E5	N2010G					
Z0ND	E5-411	N2620G					
Z0NX	E5-471	N281G					
Z0NY	E5-511	N282G					
Z0NZ	E5-521	N4620G					
Z0P0	E5-551	N4630G					
	E5-571	X2610					
	E5-572	X2610G					
	E5-721	X2611G					
	E5-731	X2630G					
	E5-771	X2631G					
		X4610G					
		X4620G					
		X4630G					
		X6610G					
		X6630G					
		Z2660G					
		Z4631G					

Table A.2: Aggregated products

Mobile PCs	Desktops	Tablets	Smartphones
Acer Aspire	Acer Aspire	Acer A1	Apple iPhone 4/4S
Acer Aspire E	Acer Veriton	Acer B1	Apple iPhone 5/5C/5S
Acer Aspire V	Apple Imac	Apple Ipad	Apple iPhone 5S/5C//5S
Acer Travelmate	Apple Mac Mini	Apple Ipad Mini	HTC Desire
Apple Mac Air	Asus All/Top/Box/Other	Apple Ipad Retina	LG Optimus
Apple Mac Pro	HP Pavilion/Proliant	Asus Google Nexus	Nokia 500
Asus EEE/F/G	Lenovo Edge	Asus Memo Pad	Nokia 600
Asus K/N	Lenovo Essential/Idea/Think	Samsung Galaxy Note 10.1	Nokia 700/800
Asus S		Samsung Galaxy Tab 2	Nokia 900
Asus X		Samsung Galaxy Tab 3	Samsung Galaxy ACE
Asus Zenbook		Sony Xperia	Samsung Galaxy S 4
Fujitsu Lifebook			Samsung Galaxy S II
HP Elitebook			Samsung Galaxy S III
HP Probook			
Lenovo Edge			
Lenovo Essential			
Toshiba Satellite C			

Figure A.1: Differences in average prices relative to Germany



Notes: The average cross-country price differences with respect to a base country (Germany) are computed as averages of $q^k_{i,c,t} = \exp(\theta^k_{i,c,t} - \theta^k_{i,B,t})$ over products i by country and channel, where $\theta^k_{i,c,t}$ is estimated based on the regression in the text.

Table A.3: Convergence regressions for mobile PCs: online versus offline

	Apple Online	Offline	Asus Online	Offline	Acer Online	Offline	Other Online	Offline
Lagged price	-0.440	-0.428	-0.184	-0.277	-0.309	-0.253	-0.244	-0.234
	(0.065)	(0.076)	(0.054)	(0.065)	(0.058)	(0.062)	(0.053)	(0.055)
Belgium	0.028	0.040	0.014	0.031	0.021	0.024	0.019	0.025
	(0.009)	(0.011)	(0.005)	(0.008)	(0.006)	(0.007)	(0.005)	(0.007)
Denmark	0.041	0.035	0.016	0.027	0.042	0.031	0.024	0.027
	(0.010)	(0.010)	(0.007)	(0.008)	(0.009)	(0.009)	(0.006)	(0.008)
France	-0.001	0.011	-0.008	-0.010	-0.022	-0.020	-0.012	-0.011
	(0.007)	(0.008)	(0.004)	(0.005)	(0.007)	(0.007)	(0.004)	(0.004)
UK	0.030	0.021	0.010	0.006	0.007	-0.002	0.003	0.001
	(0.009)	(0.009)	(0.005)	(0.005)	(0.006)	(0.005)	(0.003)	(0.004)
Italy	0.015	0.024	-0.000	0.005	-0.011	-0.008	-0.001	0.004
	(0.008)	(0.009)	(0.004)	(0.004)	(0.006)	(0.006)	(0.003)	(0.004)
Netherlands	0.025	0.030	0.010	0.015	0.016	0.006	0.011	0.013
	(0.008)	(0.009)	(0.005)	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)
Poland	0.024	0.027	-0.012	-0.015	-0.023	-0.016	-0.018	-0.012
	(0.009)	(0.010)	(0.004)	(0.005)	(0.007)	(0.006)	(0.005)	(0.004)
Spain	0.013	0.020	0.008	0.015	-0.010	-0.002	0.004	0.009
	(0.008)	(0.008)	(0.004)	(0.005)	(0.006)	(0.005)	(0.003)	(0.004)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.258	0.304	0.123	0.252	0.285	0.205	0.129	0.214
Pesaran's CADF	0.000	0.000	0.353	0.190	0.005	0.009	0.015	0.074
Levin-Lin-Chu p-value	0.0000	0.0000	0.0003	0.2170	0.0000	0.0000	0.0033	0.0009

Table A.4: Convergence regressions for desktops: online versus offline

	Apple Online	Apple Offline	HP Online	HP Offline	Acer Online	Acer Offline	Other Online	Other Offline
Lagged price	-0.336	-0.403	-0.573	-0.358	-0.236	-0.186	-0.404	-0.296
	(0.066)	(0.071)	(0.093)	(0.065)	(0.060)	(0.052)	(0.064)	(0.054)
Belgium	0.011	0.022	0.103	0.064	0.019	0.029	0.034	0.037
	(0.008)	(0.008)	(0.018)	(0.013)	(0.010)	(0.011)	(0.007)	(0.008)
Denmark	0.029	0.032	0.073	0.033	0.042	0.037	0.044	0.034
	(0.010)	(0.009)	(0.015)	(0.010)	(0.013)	(0.013)	(0.009)	(0.009)
France	-0.006	-0.004	0.006	-0.020	-0.009	-0.008	0.006	-0.006
	(0.008)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.005)	(0.005)
UK	0.006	-0.011	0.038	0.007	-0.003	0.004	0.015	0.011
	(0.008)	(0.007)	(0.009)	(0.008)	(0.009)	(0.008)	(0.005)	(0.005)
Italy	0.005	0.010	0.015	0.004	-0.014	-0.001	-0.003	0.005
	(0.008)	(0.007)	(0.008)	(0.007)	(0.010)	(0.008)	(0.004)	(0.005)
Netherlands	0.012	0.023	0.055	0.007	0.009	0.006	0.019	0.013
	(0.008)	(0.008)	(0.012)	(0.007)	(0.009)	(0.009)	(0.006)	(0.005)
Poland	0.010	0.013	-0.006	-0.005	-0.020	-0.003	-0.020	-0.008
	(0.009)	(0.007)	(0.008)	(0.008)	(0.014)	(0.010)	(0.005)	(0.005)
Spain	-0.001	0.023	0.035	0.017	0.001	0.008	0.003	0.006
	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.005)	(0.005)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.330	0.295	0.351	0.382	0.302	0.208	0.292	0.277
Pesaran's CADF	0.000	0.000	0.002	0.000	0.014	0.177	0.000	0.000
Levin-Lin-Chu p-value	0.0000	0.0000	0.0000	0.0000	0.0015	0.0038	0.0000	0.0000

Table A.5: Convergence regressions for tablets: online versus offline

	Apple		Samsung		Asus		Other	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.423	-0.429	-0.375	-0.471	-0.310	-0.192	-0.325	-0.276
	(0.065)	(0.068)	(0.057)	(0.064)	(0.061)	(0.066)	(0.064)	(0.060)
Belgium	0.041	0.045	0.028	0.064	0.008	0.006	0.011	0.005
	(0.009)	(0.010)	(0.009)	(0.013)	(0.010)	(0.011)	(0.006)	(0.007)
Denmark	0.053	0.055	0.040	0.061	0.035	0.014	0.022	0.019
	(0.010)	(0.012)	(0.010)	(0.013)	(0.013)	(0.013)	(0.008)	(0.008)
France	0.031	0.033	0.007	0.029	0.022	0.009	-0.018	-0.014
	(0.008)	(0.009)	(0.007)	(0.010)	(0.011)	(0.011)	(0.007)	(0.008)
UK	0.011	-0.034	0.030	0.019	0.016	0.003	0.000	-0.010
	(0.007)	(0.009)	(0.009)	(0.010)	(0.011)	(0.010)	(0.006)	(0.007)
Italy	0.044	0.050	0.019	0.042	-0.007	-0.012	-0.006	-0.005
	(0.009)	(0.010)	(0.008)	(0.011)	(0.010)	(0.010)	(0.006)	(0.007)
Netherlands	0.030	0.033	0.025	0.025	0.009	-0.006	-0.010	-0.016
	(0.008)	(0.009)	(0.008)	(0.010)	(0.010)	(0.010)	(0.006)	(0.007)
Poland	0.032	0.004	-0.008	-0.053	0.011	-0.003	-0.027	-0.036
	(0.008)	(0.007)	(0.007)	(0.012)	(0.011)	(0.011)	(0.007)	(0.009)
Spain	0.017	0.021	-0.010	-0.002	-0.015	-0.017	-0.029	-0.022
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.222	0.235	0.308	0.288	0.236	0.270	0.176	0.175
Pesaran's CADF	0.000	0.002	0.000	0.002	0.001	0.000	0.154	0.280
Levin-Lin-Chu p-value	0.0001	0.0000	0.0000	0.0000	0.0000	0.0002	0.0003	0.0251

Table A.6: Convergence regressions for smartphones: online versus offline

	Apple Online	Offline	Samsung Online	Offline	Nokia Online	Offline	Other Online	Offline
Lagged price	-0.406	-0.252	-0.371	-0.480	-0.362	-0.326	-0.176	-0.127
	(0.074)	(0.063)	(0.053)	(0.059)	(0.072)	(0.061)	(0.044)	(0.032)
Belgium	0.211	0.154	0.137	0.261	0.157	0.175	0.057	0.031
	(0.055)	(0.051)	(0.029)	(0.041)	(0.039)	(0.046)	(0.024)	(0.020)
Denmark	0.229	0.158	0.168	0.264	0.204	0.216	0.081	0.052
	(0.058)	(0.053)	(0.031)	(0.041)	(0.047)	(0.053)	(0.028)	(0.023)
France	0.137	0.036	0.101	0.034	0.120	-0.001	0.033	0.006
	(0.041)	(0.034)	(0.025)	(0.026)	(0.033)	(0.032)	(0.019)	(0.015)
UK	-0.641	-0.377	-0.331	-0.533	-0.235	-0.283	-0.055	-0.047
	(0.120)	(0.101)	(0.058)	(0.076)	(0.054)	(0.072)	(0.024)	(0.029)
Italy	0.200	0.115	0.105	0.186	0.133	0.139	0.043	0.023
	(0.051)	(0.046)	(0.026)	(0.034)	(0.036)	(0.042)	(0.021)	(0.018)
Netherlands	0.209	0.150	0.115	0.211	0.147	0.156	0.053	0.032
	(0.054)	(0.051)	(0.027)	(0.036)	(0.038)	(0.044)	(0.023)	(0.019)
Poland	0.194	0.044	0.085	-0.074	0.123	-0.148	0.026	-0.064
	(0.054)	(0.034)	(0.024)	(0.029)	(0.036)	(0.046)	(0.020)	(0.021)
Spain	0.044	0.020	0.021	-0.012	-0.019	-0.134	-0.018	-0.029
	(0.035)	(0.034)	(0.021)	(0.026)	(0.028)	(0.040)	(0.017)	(0.018)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.364	0.344	0.290	0.326	0.420	0.296	0.216	0.252
Pesaran's CADF	0.014	0.072	0.042	0.767	0.000	0.013	0.211	0.371
Levin-Lin-Chu p-value	0.0003	0.0004	0.0000	0.0003	0.0000	0.0000	0.0600	0.1988

Table A.7: Convergence regressions for mobile PCs: difference online - offline

	Apple	Asus	Acer	Other
Lagged price	-0.703	-0.627	-0.662	-0.655
	(0.099)	(0.094)	(0.099)	(0.093)
Belgium	-0.023	-0.024	-0.017	-0.019
	(0.007)	(0.005)	(0.006)	(0.004)
Denmark	0.006	-0.004	0.009	-0.016
	(0.006)	(0.004)	(0.006)	(0.004)
France	-0.021	-0.001	0.006	-0.004
	(0.007)	(0.004)	(0.006)	(0.003)
UK	0.014	0.018	0.023	0.007
	(0.007)	(0.005)	(0.007)	(0.003)
Italy	-0.015	-0.008	0.000	-0.013
	(0.007)	(0.004)	(0.006)	(0.004)
Netherlands	-0.009	0.001	0.017	-0.009
	(0.007)	(0.004)	(0.006)	(0.003)
Poland	-0.008	-0.005	-0.008	-0.015
	(0.007)	(0.004)	(0.006)	(0.004)
Spain	-0.012	-0.005	-0.010	-0.012
	(0.007)	(0.004)	(0.006)	(0.004)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280
R-squared	0.434	0.326	0.416	0.360
Pesaran's CADF	0.000	0.000	0.000	0.000
Levin-Lin-Chu p-value	0.0000	0.0000	0.0000	0.0000

Table A.8: Convergence regressions for desktops: difference online - offline

	Apple	HP	Acer	Other
Lagged price	-0.494	-0.407	-0.766	-0.533
	(0.085)	(0.072)	(0.094)	(0.074)
Belgium	-0.012	0.002	-0.045	-0.021
	(0.008)	(0.008)	(0.008)	(0.005)
Denmark	0.004	0.011	-0.018	-0.006
	(0.007)	(0.008)	(0.007)	(0.005)
France	-0.004	0.025	-0.001	0.014
	(0.007)	(0.009)	(0.007)	(0.005)
UK	0.023	0.022	-0.025	0.003
	(0.009)	(0.010)	(0.007)	(0.004)
Italy	-0.005	0.005	-0.048	-0.014
	(0.007)	(0.008)	(0.009)	(0.005)
Netherlands	-0.011	0.031	0.006	0.001
	(0.007)	(0.010)	(0.007)	(0.004)
Poland	0.002	0.003	-0.049	-0.015
	(0.007)	(0.008)	(0.009)	(0.005)
Spain	-0.029	0.006	-0.039	-0.008
	(0.008)	(0.008)	(0.009)	(0.004)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280
R-squared	0.375	0.465	0.436	0.399
Pesaran's CADF	0.000	0.000	0.000	0.002
Levin-Lin-Chu p-value	0.0000	0.0000	0.0000	0.0000

Table A.9: Convergence regressions for tablets: difference online - offline

	Apple	Samsung	Asus	Other
Lagged price	-0.409	-0.595	-0.577	-0.441
	(0.070)	(0.081)	(0.080)	(0.072)
Belgium	-0.003	-0.031	-0.012	0.008
	(0.007)	(0.010)	(0.010)	(0.006)
Denmark	0.000	-0.013	0.006	-0.002
	(0.007)	(0.009)	(0.010)	(0.005)
France	-0.002	-0.022	0.004	0.000
	(0.007)	(0.009)	(0.010)	(0.005)
UK	0.043	0.027	0.014	0.017
	(0.010)	(0.009)	(0.010)	(0.006)
Italy	-0.005	-0.020	0.003	0.001
	(0.007)	(0.009)	(0.010)	(0.005)
Netherlands	-0.003	0.009	0.014	0.012
	(0.007)	(0.009)	(0.010)	(0.006)
Poland	0.025	0.061	0.008	0.019
	(0.009)	(0.014)	(0.010)	(0.006)
Spain	-0.003	-0.010	-0.008	-0.002
	(0.007)	(0.009)	(0.010)	(0.005)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280
R-squared	0.279	0.361	0.322	0.224
Pesaran's CADF	0.020	0.000	0.000	0.044
Levin-Lin-Chu p-value	0.0000	0.0000	0.0000	0.0043

Table A.10: Convergence regressions for smartphones: difference online - offline

	Apple	Samsung	Nokia	Other
Lagged price	-0.398	-0.542	-0.385	-0.225
	(0.074)	(0.066)	(0.063)	(0.046)
Belgium	-0.034	-0.093	-0.043	0.001
	(0.046)	(0.029)	(0.034)	(0.020)
Denmark	-0.026	-0.056	-0.040	-0.004
	(0.046)	(0.028)	(0.034)	(0.020)
France	0.097	0.106	0.128	0.049
	(0.051)	(0.031)	(0.040)	(0.025)
UK	-0.033	0.103	0.085	0.059
	(0.046)	(0.030)	(0.042)	(0.027)
Italy	0.012	-0.057	-0.024	-0.000
	(0.046)	(0.028)	(0.034)	(0.020)
Netherlands	-0.032	-0.070	-0.031	0.001
	(0.046)	(0.028)	(0.034)	(0.020)
Poland	0.146	0.209	0.307	0.144
	(0.061)	(0.040)	(0.065)	(0.038)
Spain	0.020	0.036	0.122	0.033
	(0.046)	(0.027)	(0.036)	(0.021)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280
R-squared	0.331	0.407	0.463	0.155
Pesaran's CADF	0.000	0.058	0.003	0.273
Levin-Lin-Chu p-value	0.0000	0.0004	0.0000	0.0176

Table A.11: Common versus different currency countries: Euro-zone

	Portable PCs		Desktops		Tablets		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.300	-0.316	-0.652	-0.375	-0.580	-0.529	-0.202	-0.132
	(0.064)	(0.086)	(0.119)	(0.090)	(0.096)	(0.094)	(0.049)	(0.045)
Belgium	0.022	0.034	0.073	0.053	0.038	0.036	0.076	0.052
	(0.005)	(0.009)	(0.014)	(0.013)	(0.007)	(0.008)	(0.024)	(0.024)
France	-0.014	-0.014	0.003	-0.010	0.001	0.003	0.051	0.012
	(0.004)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)	(0.016)	(0.011)
Italy	-0.002	0.004	-0.003	0.006	0.015	0.015	0.061	0.038
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.020)	(0.020)
Netherlands	0.014	0.016	0.039	0.015	0.011	0.000	0.070	0.048
	(0.004)	(0.005)	(0.008)	(0.005)	(0.004)	(0.004)	(0.022)	(0.022)
Spain	0.004	0.010	0.011	0.013	-0.020	-0.015	-0.001	-0.026
	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.012)	(0.014)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	175	175	175	175	175	175	175	175
R-squared	0.287	0.286	0.326	0.237	0.185	0.297	0.190	0.159
Pesaran's CADF	0.011	0.051	0.018	0.090	0.034	0.048	0.278	0.589
Levin-Lin-Chu p-value	0.0007	0.0006	0.0000	0.0000	0.0017	0.0000	0.0000	0.3843

Table A.12: Common versus different currency countries: non-Euro-zone

	Portable PCs		Desktops		Tablets		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.208	-0.190	-0.218	-0.232	-0.231	-0.347	-0.104	-0.118
	(0.084)	(0.076)	(0.081)	(0.086)	(0.091)	(0.096)	(0.067)	(0.057)
Denmark	0.021	0.021	0.024	0.025	0.022	0.033	0.046	0.056
	(0.009)	(0.010)	(0.011)	(0.013)	(0.010)	(0.012)	(0.037)	(0.036)
UK	0.005	0.001	0.008	0.006	0.006	-0.010	-0.056	-0.075
	(0.004)	(0.003)	(0.005)	(0.005)	(0.006)	(0.007)	(0.052)	(0.061)
Poland	-0.014	-0.009	-0.010	-0.005	-0.006	-0.023	0.016	-0.030
	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.008)	(0.025)	(0.026)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	105	105	105	105	105	105	105	105
R-squared	0.139	0.181	0.117	0.212	0.140	0.142	0.234	0.262
Pesaran's CADF	0.330	0.016	0.161	0.379	0.564	0.212	0.695	0.013
Levin-Lin-Chu p-value	0.4586	0.0744	0.2186	0.2977	0.1450	0.2212	0.7373	0.0053

Appendix B: One-stage regressions

Table B.1: Convergence regressions: online versus offline

	Portable PCs		Desktops		Tablets		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.210	-0.189	-0.288	-0.254	-0.273	-0.170	-0.205	-0.182
	(0.005)	(0.004)	(0.008)	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)
BE	0.014	0.022	0.032	0.041	0.022	0.017	0.061	0.058
	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.004)	(0.009)	(0.010)
DK	0.020	0.016	0.040	0.034	0.026	0.010	0.081	0.081
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.010)
FR	-0.007	-0.010	-0.001	-0.006	0.001	-0.001	0.037	-0.015
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)
UK	0.007	-0.001	0.018	0.010	0.010	-0.006	-0.119	-0.163
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.011)
IT	0.004	0.004	0.005	0.007	0.013	0.005	0.042	0.035
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.004)	(0.008)	(0.009)
NL	0.009	0.011	0.023	0.020	0.013	-0.001	0.055	0.050
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.009)
PL	-0.015	-0.010	-0.008	-0.004	-0.002	-0.019	0.033	-0.061
	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.004)	(0.009)	(0.010)
ES	0.004	0.005	0.005	0.015	-0.008	-0.012	-0.018	-0.066
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.008)	(0.009)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Product fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	49,050	49,050	21,459	21,459	20,794	20,794	24,212	24,212
R-squared	0.232	0.223	0.259	0.276	0.166	0.154	0.210	0.172

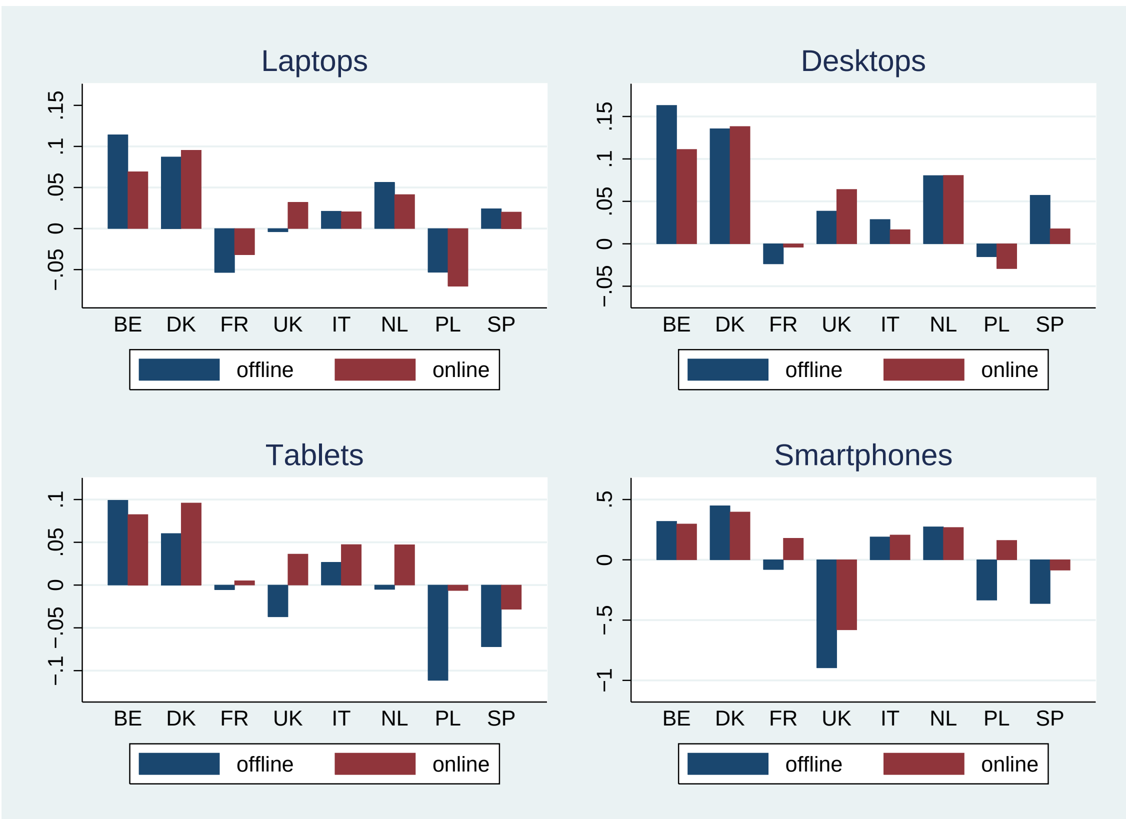
Notes: Parameter estimates are based on convergence regression (1) including a set of product fixed effects at the category level.

Table B.2: Convergence regressions: difference online - offline

	Portable PCs	Desktops	Tablets	Smartphones
Lagged price	-0.368	-0.441	-0.303	-0.249
	(0.007)	(0.010)	(0.009)	(0.006)
BE	0.009	-0.005	-0.023	-0.047
	(0.032)	(0.025)	(0.023)	(0.049)
DK	0.022	0.010	-0.013	-0.054
	(0.032)	(0.025)	(0.023)	(0.049)
FR	0.028	0.025	-0.021	0.032
	(0.032)	(0.024)	(0.023)	(0.049)
DE	0.024	0.015	-0.020	-0.045
	(0.032)	(0.024)	(0.023)	(0.049)
UK	0.032	0.027	0.001	0.039
	(0.032)	(0.024)	(0.023)	(0.049)
IT	0.021	0.007	-0.019	-0.036
	(0.032)	(0.025)	(0.023)	(0.049)
NL	0.020	0.019	-0.009	-0.039
	(0.032)	(0.024)	(0.023)	(0.049)
PL	0.017	0.002	0.004	0.096
	(0.032)	(0.025)	(0.023)	(0.049)
ES	0.019	-0.003	-0.018	0.026
	(0.032)	(0.025)	(0.023)	(0.049)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)
Product fixed effects	yes	yes	yes	yes
Observations	46,691	19,888	20,111	24,212
R-squared	0.283	0.331	0.207	0.210

Notes: Parameter estimates are based on convergence regression (2) including a set of product fixed effects at the category level.

Figure B.1: Long-term price differences



Notes: Long-term prie differences computed from $\alpha_c^k/(-\beta^k)$, based on the parameter estimates of convergence regression (1) including a set of product fixed effects shown in Table B.1.

Appendix C: Heterogeneity

Table C.1: Main brands market shares

	Portable PCs	Desktops	Tablets	Smartphones
Acer	14.79%	7.93%	2.58%	0.56%
Amazon Kindle			2.18%	
Apple	5.90%	6.85%	34.05%	23.43%
Asus	15.99%	3.10%	6.77%	0.07%
Dell	3.07%	7.20%	0.05%	0.00%
Fujitsu	1.73%	10.42%	0.01%	
HP	17.93%	34.83%	0.44%	
HTC			0.07%	4.21%
Lenovo	13.70%	14.04%	2.05%	0.01%
LG	0.00%	0.08%	0.22%	4.72%
Nokia			0.02%	6.78%
Samsung	5.46%	0.35%	26.68%	40.44%
Sony	4.15%	0.26%	0.71%	8.45%
Toshiba	9.68%	0.04%	0.19%	
Other	7.60%	14.90%	23.98%	11.33%

Notes: Market shares in the entire period between January 2012 and March 2015.

Table C.2: Main brands - share of online sales

	Portable PCs	Desktops	Tablets	Smartphones
Acer	26.2%	21.9%	22.0%	24.8%
Amazon Kindle			14.6%	
Apple	16.8%	17.0%	18.5%	18.4%
Asus	24.2%	27.3%	26.9%	41.1%
Dell	21.1%	13.9%	16.5%	15.2%
Fujitsu	23.4%	7.2%	37.3%	
HP	18.4%	12.1%	15.6%	
HTC			57.5%	21.6%
Lenovo	30.4%	20.2%	26.7%	25.8%
LG	24.7%	53.7%	30.8%	13.4%
Nokia			59.9%	14.2%
Samsung	22.4%	24.5%	23.1%	16.1%
Sony	19.1%	24.4%	26.0%	15.0%
Toshiba	20.2%	33.0%	30.4%	
All	23.0%	15.7%	20.1%	16.9%

Notes: Share of online sales in the entire period between January 2012 and March 2015.

Table C.3: Convergence regressions: online versus offline for small brands

	Portable PCs		Desktops		Tablets		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.259	-0.258	-0.305	-0.274	-0.312	-0.293	-0.188	-0.123
	(0.066)	(0.064)	(0.070)	(0.054)	(0.063)	(0.063)	(0.046)	(0.033)
BE	0.013	0.019	0.017	0.026	0.007	0.003	0.059	0.027
	(0.006)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.025)	(0.020)
DK	0.020	0.024	0.025	0.025	0.019	0.020	0.083	0.047
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.028)	(0.023)
FR	-0.020	-0.012	-0.007	-0.010	-0.021	-0.018	0.033	0.004
	(0.006)	(0.005)	(0.006)	(0.006)	(0.008)	(0.009)	(0.019)	(0.017)
UK	0.001	-0.001	0.010	0.010	-0.007	-0.019	-0.046	-0.042
	(0.004)	(0.005)	(0.007)	(0.006)	(0.007)	(0.009)	(0.023)	(0.029)
IT	-0.008	-0.000	-0.018	-0.005	-0.008	-0.006	0.046	0.022
	(0.005)	(0.004)	(0.007)	(0.006)	(0.007)	(0.008)	(0.022)	(0.019)
NL	0.006	0.007	0.009	0.010	-0.011	-0.019	0.055	0.029
	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.009)	(0.023)	(0.019)
PL	-0.021	-0.014	-0.032	-0.025	-0.034	-0.043	0.025	-0.058
	(0.006)	(0.005)	(0.009)	(0.007)	(0.008)	(0.011)	(0.020)	(0.021)
ES	-0.004	0.004	-0.005	-0.001	-0.030	-0.026	-0.031	-0.032
	(0.004)	(0.005)	(0.006)	(0.006)	(0.009)	(0.010)	(0.018)	(0.019)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.203	0.207	0.283	0.231	0.228	0.196	0.225	0.220
Pesaran's CADF	0.000	0.027	0.002	0.000	0.118	0.203	0.119	0.630
Levin-Lin-Chu p-value	0.0002	0.0003	0.0000	0.0000	0.0018	0.0004	0.0197	0.2256

Notes: Parameter estimates are based on convergence regression (1) for small brands.

Table C.4: Convergence regressions: online versus offline for large brands

	Portable PCs		Desktops		Tablets		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.264	-0.233	-0.295	-0.246	-0.241	-0.267	-0.318	-0.260
	(0.050)	(0.057)	(0.072)	(0.061)	(0.055)	(0.059)	(0.045)	(0.048)
BE	0.021	0.027	0.038	0.039	0.018	0.025	0.133	0.142
	(0.005)	(0.007)	(0.010)	(0.010)	(0.007)	(0.008)	(0.024)	(0.032)
DK	0.028	0.027	0.038	0.029	0.026	0.028	0.163	0.158
	(0.006)	(0.008)	(0.011)	(0.009)	(0.008)	(0.009)	(0.027)	(0.034)
FR	-0.010	-0.010	0.002	-0.009	0.009	0.012	0.097	0.022
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.018)	(0.017)
UK	0.007	0.002	0.014	0.008	0.011	-0.004	-0.305	-0.275
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.005)	(0.048)	(0.061)
IT	0.001	0.004	0.003	0.006	0.012	0.015	0.108	0.104
	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.006)	(0.021)	(0.026)
NL	0.014	0.013	0.021	0.011	0.011	0.008	0.119	0.123
	(0.004)	(0.005)	(0.007)	(0.005)	(0.006)	(0.006)	(0.022)	(0.029)
PL	-0.017	-0.012	-0.007	0.000	0.004	-0.010	0.099	-0.062
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.020)	(0.024)
ES	0.006	0.009	0.009	0.013	-0.005	-0.003	0.028	-0.028
	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.014)	(0.017)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.176	0.189	0.266	0.311	0.178	0.225	0.303	0.212
Pesaran's CADF	0.026	0.283	0.001	0.004	0.000	0.000	0.001	0.813
Levin-Lin-Chu p-value	0.0011	0.0140	0.0000	0.0000	0.0002	0.0000	0.0000	0.0008

Notes: Parameter estimates are based on convergence regression (1) for large brands.

Table C.5: Convergence regressions: difference online - offline

	Small				Large			
VARIABLES	Portable PCs	Desktops	Tablets	Smart	Portable PCs	Desktops	Tablets	Smart
Lagged price	-0.634	-0.605	-0.376	-0.255	-0.501	-0.479	-0.374	-0.301
	(0.080)	(0.074)	(0.067)	(0.046)	(0.080)	(0.071)	(0.064)	(0.040)
BE	-0.011	-0.028	-0.000	-0.005	-0.019	-0.026	-0.010	-0.015
	(0.004)	(0.005)	(0.005)	(0.017)	(0.004)	(0.005)	(0.004)	(0.015)
DK	-0.011	-0.015	-0.010	-0.011	-0.008	-0.012	-0.002	-0.004
	(0.004)	(0.005)	(0.005)	(0.017)	(0.003)	(0.004)	(0.004)	(0.015)
FR	-0.015	0.001	-0.008	0.052	0.000	0.004	-0.006	0.090
	(0.004)	(0.004)	(0.005)	(0.023)	(0.002)	(0.003)	(0.004)	(0.020)
UK	0.001	-0.005	-0.006	-0.009	-0.002	-0.014	-0.002	0.025
	(0.003)	(0.004)	(0.005)	(0.017)	(0.002)	(0.004)	(0.004)	(0.015)
IT	0.008	-0.007	0.010	0.065	0.008	-0.002	0.021	0.058
	(0.004)	(0.004)	(0.005)	(0.025)	(0.003)	(0.003)	(0.005)	(0.018)
NL	-0.013	-0.029	-0.007	-0.009	-0.008	-0.020	-0.005	0.006
	(0.004)	(0.005)	(0.005)	(0.017)	(0.003)	(0.005)	(0.004)	(0.015)
PL	-0.003	-0.010	0.004	-0.006	-0.004	0.002	0.003	-0.006
	(0.003)	(0.005)	(0.005)	(0.017)	(0.002)	(0.004)	(0.004)	(0.015)
ES	-0.013	-0.020	0.008	0.137	-0.010	-0.025	0.020	0.193
	(0.004)	(0.006)	(0.005)	(0.032)	(0.003)	(0.005)	(0.006)	(0.034)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	315	315	315	315	315	315	315	315
R-squared	0.314	0.403	0.243	0.213	0.327	0.402	0.282	0.300
Pesaran's CADF	0.000	0.001	0.001	0.000	0.000	0.000	0.001	0.005
Levin-Lin-Chu p-value	0.0000	0.0000	0.0002	0.0718	0.0000	0.0000	0.0000	0.0001

Notes: Parameter estimates are based on convergence regression (1) for small and large brands.

Table C.6: Convergence regressions: online versus offline for 'offline brands'

	Portable PCs		Desktops		Tablets		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.506	-0.502	-0.307	-0.152	-0.405	-0.335	-0.347	-0.202
	(0.092)	(0.084)	(0.069)	(0.050)	(0.070)	(0.061)	(0.065)	(0.039)
BE	0.019	0.015	0.025	-0.001	-0.016	-0.002	0.119	0.046
	(0.007)	(0.006)	(0.014)	(0.013)	(0.011)	(0.011)	(0.038)	(0.024)
DK	0.035	0.038	0.044	0.005	-0.008	0.002	0.144	0.066
	(0.008)	(0.009)	(0.016)	(0.014)	(0.011)	(0.011)	(0.039)	(0.026)
FR	-0.045	-0.022	-0.026	-0.020	-0.063	-0.041	0.064	-0.008
	(0.010)	(0.007)	(0.013)	(0.013)	(0.016)	(0.014)	(0.031)	(0.021)
UK	0.001	-0.005	0.041	0.019	-0.015	-0.015	-0.052	-0.048
	(0.005)	(0.006)	(0.014)	(0.013)	(0.011)	(0.011)	(0.031)	(0.024)
IT	-0.016	-0.002	-0.016	-0.022	-0.046	-0.032	0.088	0.037
	(0.006)	(0.006)	(0.012)	(0.013)	(0.014)	(0.012)	(0.034)	(0.023)
NL	-0.002	0.003	0.014	-0.003	-0.032	-0.030	0.112	0.045
	(0.005)	(0.006)	(0.013)	(0.013)	(0.012)	(0.012)	(0.036)	(0.023)
PL	-0.011	0.005	-0.025	-0.030	-0.085	-0.074	0.038	-0.107
	(0.006)	(0.006)	(0.013)	(0.013)	(0.017)	(0.016)	(0.031)	(0.026)
ES	-0.008	0.013	-0.004	-0.017	-0.063	-0.041	-0.106	-0.074
	(0.005)	(0.006)	(0.012)	(0.013)	(0.016)	(0.014)	(0.035)	(0.026)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.253	0.196	0.292	0.329	0.326	0.285	0.306	0.185
Pesaran's CADF	0.001	0.000	0.000	0.000	0.367	0.347	0.749	0.116
Levin-Lin-Chu p-value	0.0000	0.0000	0.0000	0.0000	0.0137	0.0059	0.0004	0.0005

Notes: Parameter estimates are based on convergence regression (1) for 'offline brands'.

Table C.7: Convergence regressions: online versus offline for 'online brands'

	Portable PCs		Desktops		Tablets		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.167	-0.205	-0.357	-0.370	-0.418	-0.383	-0.136	-0.164
	(0.058)	(0.056)	(0.067)	(0.065)	(0.067)	(0.074)	(0.052)	(0.045)
BE	0.009	0.022	0.007	0.039	0.024	0.007	0.032	0.057
	(0.008)	(0.009)	(0.008)	(0.010)	(0.008)	(0.009)	(0.028)	(0.032)
DK	0.011	0.021	0.018	0.029	0.051	0.045	0.056	0.092
	(0.009)	(0.010)	(0.008)	(0.009)	(0.012)	(0.013)	(0.035)	(0.038)
FR	-0.014	-0.013	-0.000	-0.005	-0.017	-0.017	0.019	0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.010)	(0.022)	(0.024)
UK	-0.001	-0.003	-0.014	-0.011	-0.008	-0.028	-0.038	-0.107
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.011)	(0.027)	(0.050)
IT	-0.007	-0.002	-0.022	-0.002	-0.005	-0.000	0.027	0.047
	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)	(0.009)	(0.025)	(0.029)
NL	0.007	0.009	0.005	0.016	-0.007	-0.015	0.026	0.054
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.026)	(0.030)
PL	-0.024	-0.025	-0.039	-0.032	-0.027	-0.041	0.016	-0.060
	(0.009)	(0.008)	(0.010)	(0.008)	(0.008)	(0.011)	(0.024)	(0.028)
ES	-0.003	0.000	-0.010	0.000	-0.036	-0.036	0.001	-0.023
	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)	(0.011)	(0.019)	(0.025)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.281	0.256	0.355	0.246	0.241	0.207	0.401	0.271
Pesaran's CADF	0.000	0.002	0.007	0.001	0.020	0.005	0.001	0.849
Levin-Lin-Chu p-value	0.0003	0.0003	0.0000	0.0000	0.0000	0.0000	0.0003	0.4371

Notes: Parameter estimates are based on convergence regression (1) for 'online brands'.

Table C.8: Convergence regressions: difference online - offline

	'Offline brands'				'Online brands'			
	Portable PCs	Desktops	Tablets	Smart	Portable PCs	Desktops	Tablets	Smart
Lagged price	-0.573	-0.496	-0.628	-0.519	-0.523	-0.643	-0.401	-0.217
	(0.092)	(0.071)	(0.088)	(0.060)	(0.076)	(0.085)	(0.070)	(0.055)
BE	0.004	0.000	-0.010	-0.003	-0.021	-0.051	0.005	-0.006
	(0.005)	(0.011)	(0.007)	(0.025)	(0.006)	(0.008)	(0.007)	(0.022)
DK	-0.006	0.001	-0.010	-0.024	-0.012	-0.020	-0.011	-0.015
	(0.005)	(0.011)	(0.008)	(0.025)	(0.005)	(0.006)	(0.007)	(0.022)
FR	-0.028	-0.018	-0.014	0.114	-0.003	0.007	-0.009	0.046
	(0.006)	(0.011)	(0.008)	(0.030)	(0.005)	(0.005)	(0.007)	(0.029)
UK	-0.001	-0.019	0.004	-0.037	0.002	-0.001	-0.011	0.006
	(0.005)	(0.011)	(0.007)	(0.025)	(0.005)	(0.005)	(0.007)	(0.022)
IT	0.006	-0.007	0.013	0.042	0.008	-0.006	0.011	0.083
	(0.005)	(0.011)	(0.008)	(0.026)	(0.005)	(0.005)	(0.007)	(0.040)
NL	-0.016	-0.013	-0.004	-0.024	-0.008	-0.034	-0.015	-0.002
	(0.005)	(0.011)	(0.008)	(0.025)	(0.005)	(0.007)	(0.007)	(0.022)
PL	-0.007	0.005	0.011	-0.009	0.002	-0.019	-0.002	-0.009
	(0.005)	(0.011)	(0.007)	(0.025)	(0.005)	(0.006)	(0.007)	(0.022)
ES	-0.019	-0.031	0.015	0.269	-0.004	-0.017	0.006	0.126
	(0.005)	(0.013)	(0.008)	(0.040)	(0.005)	(0.006)	(0.007)	(0.042)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	315	315	315	315	315	315	315	315
R-squared	0.377	0.403	0.328	0.279	0.327	0.365	0.280	0.248
Pesaran's CADF	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Levin-Lin-Chu p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0991

Notes: Parameter estimates are based on convergence regression (1) for 'online' and 'offline' brands.

Table C.9: Convergence regressions: online versus offline for low-priced products

	Portable PCs		Desktops		Tablets		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.315	-0.315	-0.282	-0.286	-0.374	-0.311	-0.217	-0.138
	(0.056)	(0.064)	(0.060)	(0.055)	(0.066)	(0.061)	(0.045)	(0.034)
BE	0.031	0.041	0.025	0.048	0.017	0.012	0.068	0.033
	(0.006)	(0.009)	(0.007)	(0.010)	(0.007)	(0.007)	(0.025)	(0.020)
DK	0.042	0.040	0.036	0.044	0.013	0.008	0.094	0.046
	(0.008)	(0.009)	(0.009)	(0.010)	(0.007)	(0.007)	(0.027)	(0.022)
FR	-0.011	-0.011	0.002	0.001	-0.006	-0.003	0.038	0.006
	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)	(0.019)	(0.015)
UK	0.012	0.003	0.009	0.009	0.005	-0.007	-0.060	-0.036
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.022)	(0.027)
IT	0.000	0.003	-0.003	0.012	-0.008	-0.008	0.051	0.024
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.007)	(0.022)	(0.018)
NL	0.023	0.022	0.017	0.019	-0.003	-0.011	0.062	0.031
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.023)	(0.019)
PL	-0.018	-0.015	-0.016	-0.002	-0.039	-0.047	0.031	-0.060
	(0.004)	(0.004)	(0.005)	(0.004)	(0.008)	(0.010)	(0.020)	(0.025)
ES	0.010	0.014	0.003	0.016	-0.025	-0.019	-0.005	-0.028
	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)	(0.008)	(0.018)	(0.017)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.266	0.279	0.301	0.238	0.169	0.209	0.229	0.220
Pesaran's CADF	0.137	0.166	0.081	0.300	0.034	0.057	0.000	0.258
Levin-Lin-Chu p-value	0.0024	0.0009	0.0020	0.0000	0.0000	0.0011	0.0031	0.0039

Notes: Parameter estimates are based on convergence regression (1) for low-priced products.

Table C.10: Convergence regressions: online versus offline for high-priced products

	Portable PCs		Desktops		Tablets		Smartphones	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline
Lagged price	-0.255	-0.187	-0.388	-0.367	-0.328	-0.390	-0.262	-0.209
	(0.054)	(0.056)	(0.071)	(0.072)	(0.057)	(0.064)	(0.053)	(0.050)
BE	0.013	0.014	0.049	0.043	0.026	0.037	0.106	0.111
	(0.004)	(0.006)	(0.011)	(0.010)	(0.007)	(0.008)	(0.027)	(0.033)
DK	0.019	0.016	0.038	0.027	0.041	0.052	0.135	0.131
	(0.006)	(0.007)	(0.009)	(0.009)	(0.008)	(0.011)	(0.032)	(0.037)
FR	-0.015	-0.012	-0.002	-0.022	0.010	0.013	0.081	0.019
	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)	(0.021)	(0.018)
UK	0.001	0.001	0.014	0.002	0.009	-0.016	-0.264	-0.247
	(0.003)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)	(0.057)	(0.068)
IT	-0.001	0.004	-0.002	-0.005	0.020	0.027	0.088	0.084
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)	(0.023)	(0.028)
NL	0.005	0.005	0.022	0.004	0.016	0.012	0.097	0.098
	(0.004)	(0.004)	(0.007)	(0.005)	(0.005)	(0.006)	(0.025)	(0.030)
PL	-0.019	-0.009	-0.014	-0.015	0.011	-0.010	0.085	-0.017
	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.006)	(0.024)	(0.020)
ES	-0.001	0.003	0.011	0.005	-0.007	-0.006	0.016	-0.032
	(0.003)	(0.004)	(0.006)	(0.005)	(0.005)	(0.006)	(0.015)	(0.020)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	280	280	280	280	280	280	280	280
R-squared	0.197	0.240	0.277	0.302	0.176	0.227	0.271	0.167
Pesaran's CADF	0.006	0.005	0.000	0.000	0.014	0.012	0.183	0.512
Levin-Lin-Chu p-value	0.0001	0.0003	0.0000	0.0000	0.0057	0.0012	0.0000	0.1795

Notes: Parameter estimates are based on convergence regression (1) for high-priced products.

Table C.11: Convergence regressions: difference online - offline

	Low-priced products				High-priced products			
VARIABLES	Portable PCs	Desktops	Tablets	Smart	Portable PCs	Desktops	Tablets	Smart
Lagged price	-0.621	-0.412	-0.386	-0.249	-0.542	-0.583	-0.424	-0.263
	(0.082)	(0.066)	(0.062)	(0.035)	(0.076)	(0.081)	(0.064)	(0.050)
BE	-0.028	-0.032	-0.006	-0.004	-0.011	-0.018	-0.007	-0.015
	(0.005)	(0.006)	(0.004)	(0.015)	(0.003)	(0.005)	(0.004)	(0.016)
DK	-0.007	-0.012	-0.006	0.002	-0.010	-0.012	-0.006	-0.011
	(0.003)	(0.004)	(0.004)	(0.015)	(0.003)	(0.005)	(0.004)	(0.016)
FR	-0.011	0.000	-0.010	0.041	0.003	0.008	-0.004	0.082
	(0.003)	(0.003)	(0.005)	(0.017)	(0.002)	(0.004)	(0.004)	(0.025)
UK	-0.009	-0.001	-0.009	-0.008	0.005	-0.024	-0.002	0.019
	(0.003)	(0.003)	(0.005)	(0.015)	(0.003)	(0.005)	(0.004)	(0.016)
IT	0.009	-0.002	0.006	0.030	0.009	-0.004	0.027	0.071
	(0.003)	(0.003)	(0.004)	(0.018)	(0.003)	(0.004)	(0.005)	(0.023)
NL	-0.012	-0.022	-0.007	-0.005	-0.009	-0.018	-0.006	0.001
	(0.003)	(0.005)	(0.004)	(0.015)	(0.003)	(0.005)	(0.004)	(0.016)
PL	-0.008	-0.004	0.001	-0.006	-0.002	0.004	0.005	-0.007
	(0.003)	(0.003)	(0.004)	(0.015)	(0.002)	(0.004)	(0.004)	(0.016)
ES	-0.014	-0.022	0.008	0.156	-0.010	-0.021	0.024	0.132
	(0.003)	(0.005)	(0.004)	(0.032)	(0.003)	(0.005)	(0.006)	(0.035)
Lagged diff prices	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)	yes (3)
Observations	315	315	315	315	315	315	315	315
R-squared	0.330	0.363	0.224	0.283	0.322	0.450	0.323	0.188
Pesaran's CADF	0.001	0.001	0.000	0.000	0.000	0.000	0.025	0.001
Levin-Lin-Chu p-value	0.0000	0.0000	0.0000	0.0013	0.0000	0.0000	0.0000	0.0831

Notes: Parameter estimates are based on convergence regression (1) for low and high-priced products.