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# 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

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[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.

This conclusion is also relevant to policy makers. The share of cross-border transactions made online within the European Union is still small.[2] 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.[3] 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 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-

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[2] 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).

[3] 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.

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.[4] 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 model name. In each country and month a product can be sold online and/or through a traditional offline retail channel.[5] Sales volumes and turnover per item (product and sales channel in a month

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[4]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.

[5]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.

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.[6] 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. 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.

**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 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

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[6]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.

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.[7] 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.

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.[8] In sum, both the offline and the online channel show a considerable scope of arbitrage opportunities, which are currently not exploited.

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

[8]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

| | | 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 |

| | | 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). 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.

**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 $r_{m,c,t}^k$ 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 $\delta_m$ and a set of 702 fixed effects $\theta_{i,c,t}^k$ for distribution channel, country and period ($2 \times 9 \times 39$). We take the following logarithmic regression:

$$\log r_{m,c,t}^k = \theta_{i,c,t}^k + \delta_m + \epsilon_{m,c,t}^k$$

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 $q_{i,c,t}^k = \exp(\theta_{i,c,t}^k - \theta_{i,B,t}^k)$. First, we perform these regressions by each of the four product categories, and hence 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.[9]

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.[10] 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.

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[9]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.

[10]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

# 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.[11]  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

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[11]A fast convergence may in principle be due to arbitrage activities directly, but it may in general also be due to low adjustment costs that induce firms to re-optimize their markups quickly after shocks.

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which extent these long-term price differences 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 $p_{i,c,t}^k$ 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., $p_{i,c,t}^k = \log(q_{i,c,t}^k)$, 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 $\beta_i^k$ 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, $\beta$ is equal to zero and shocks to $p_{i,c,t}^k$ are permanent. There is convergence when $\beta$ 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 $\beta_i$ 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 $\beta_i^k$ 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.

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.

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.

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Overall, the long-term international price differences tend to be similar for the offline and online 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.

Figure 2: Long-term price differences
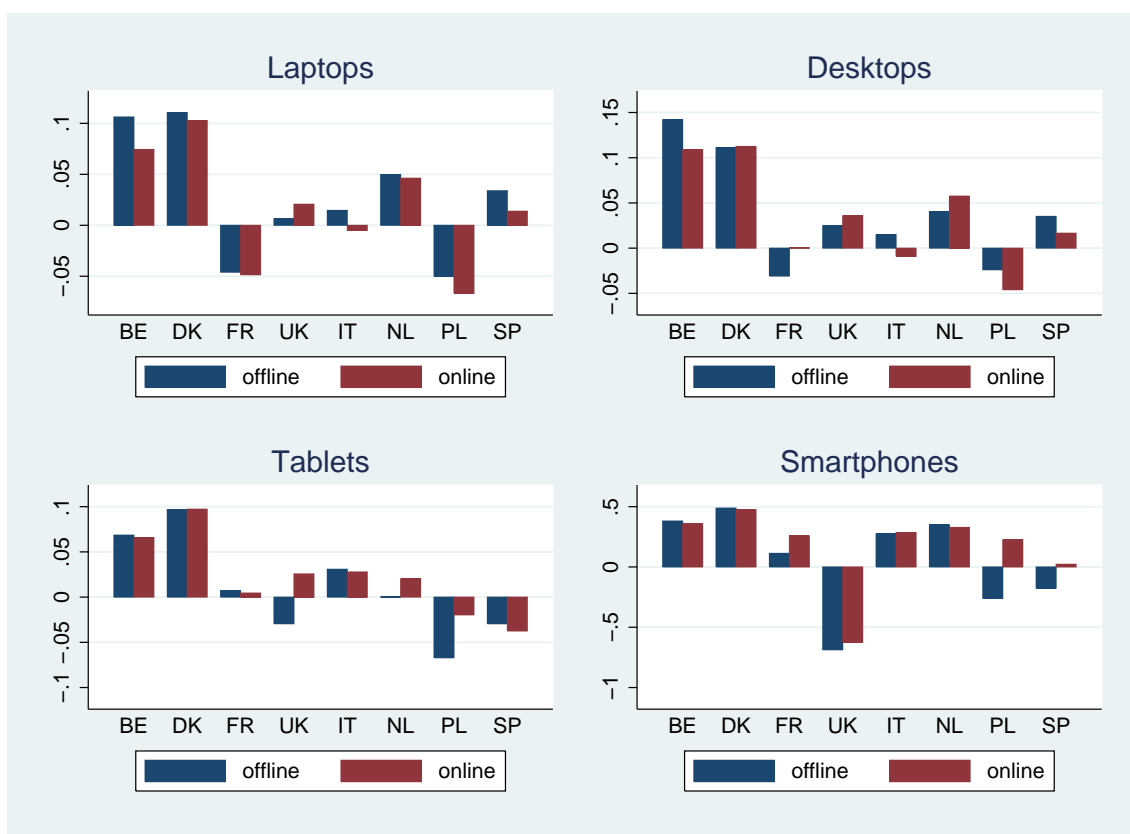


Notes: Long-term price differences computed from $\alpha_c^k/(-\beta^k)$, based on the parameter estimates of convergence regression (1) shown in Table 2.

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

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.

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.[12] A simple OLS regression of the long-

[12]We dropped 2 observations for smartphones which were outliers with high long-term price differences, though

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.

Figure 3: Long-term price differences
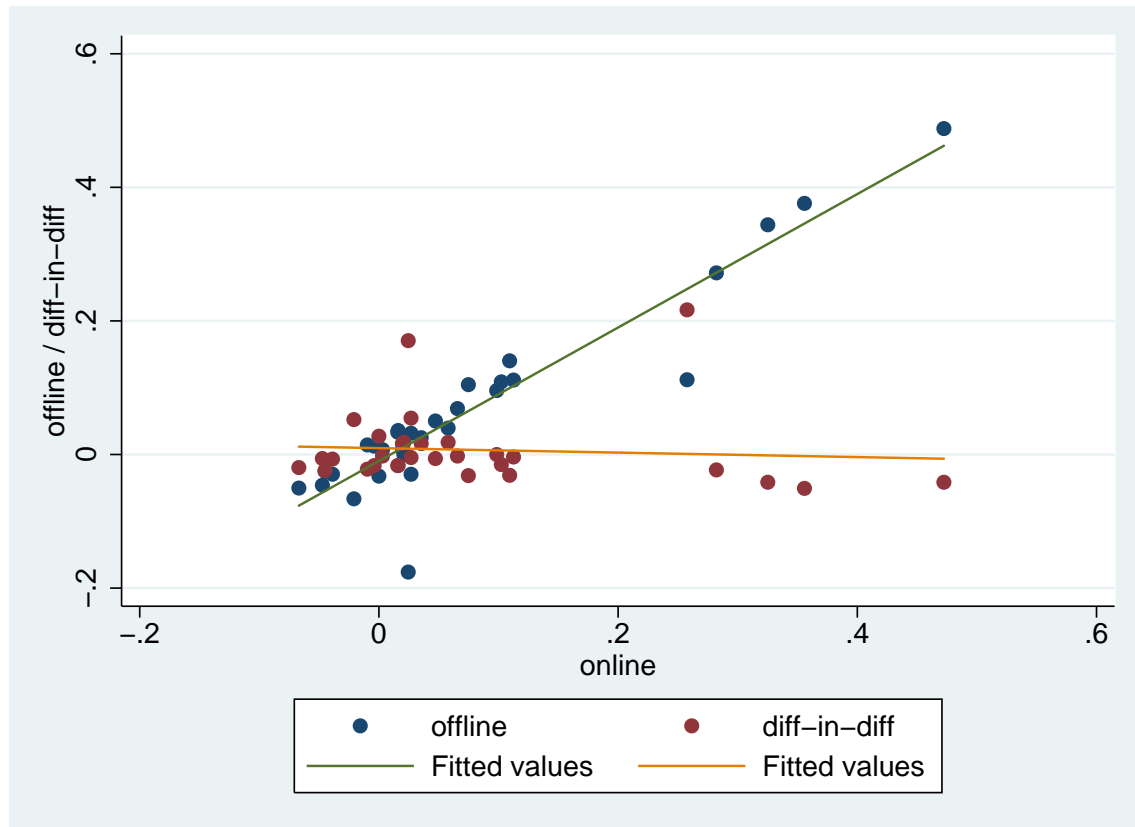
Our finding that long-term international price differences are closely comparable for the offline and online channel may shed some indirect light on the underlying sources. To the extent that cross-country differences in local distribution costs are limited in the online channel, the price differences 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

they show an entirely consistent pattern.

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. 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 model (2) was estimated after aggregating product prices to the category level in a first stage. As a robustness analysis, we have also estimated model (2) at the 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 number 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 6 in Appendix B, are comparable to what we obtained through our two-stage procedure. 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.

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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 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). 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.

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).

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).

## 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 ($\beta_i^k$, top part) and for the difference between online and offline ($\beta_i$, 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 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.[13]

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

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[13]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
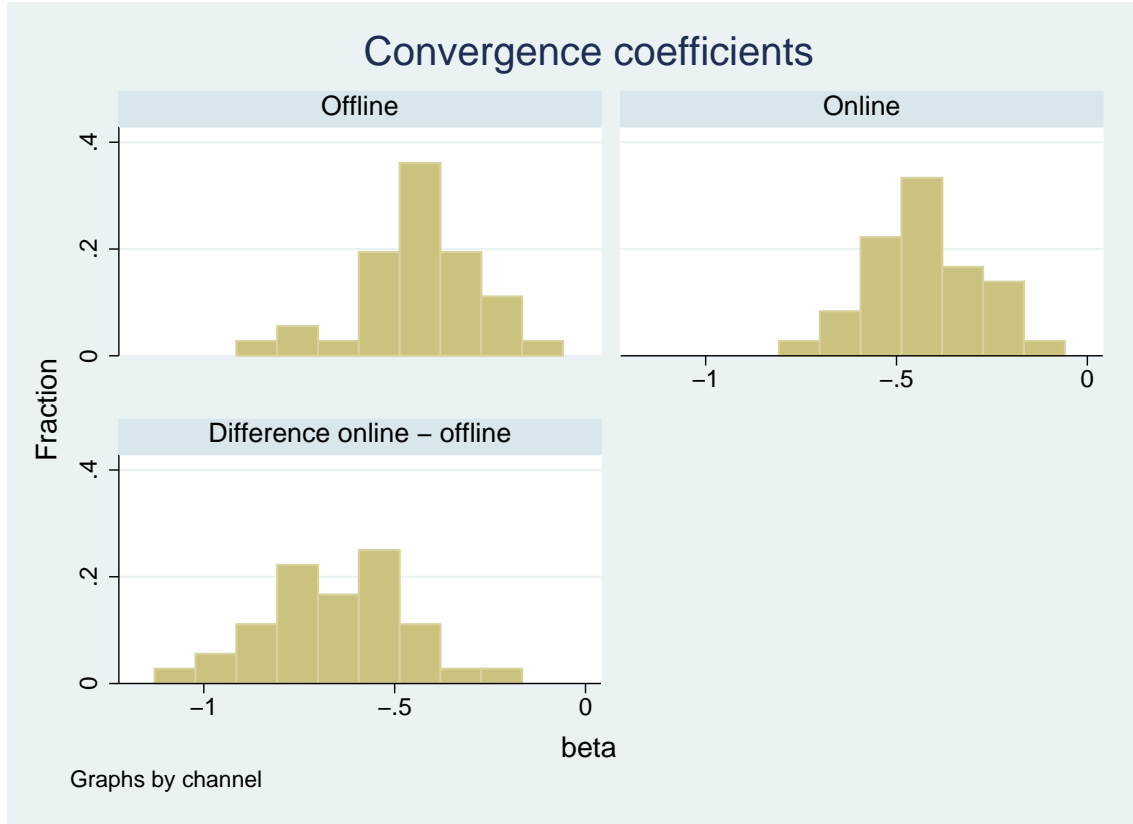


Notes: The graph plots the estimated convergence coefficients by product, based on convergence regression (1) at the product level.

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.

## 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

Figure 5: Long-term international price differences across products
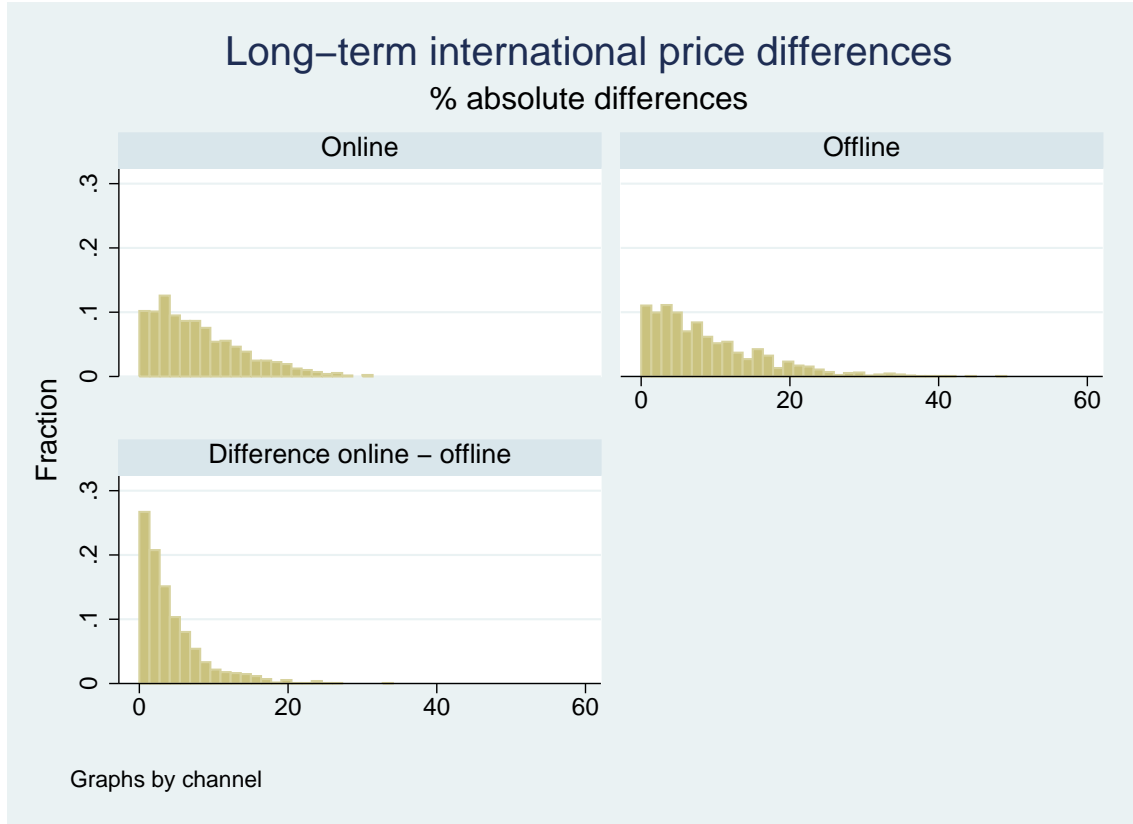


Notes: The graph plots the long-term international price differences by product and country pair, based on convergence regression (1) at the product level.

Spain) and the bottom panel considers the countries with different currencies (Denmark, Poland, the U.K. and again Germany).[14]

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, convergence appears to be on average faster within the Eurozone than between countries with different currencies.[15]

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[14]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).

[15]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.

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 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

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.

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 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

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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 | | | |

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

| | Apple | | Asus | | Acer | | Other | |
|---|---|---|---|---|---|---|---|---|
| | Online | Offline | Online | Offline | Online | Offline | 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 | | HP | | Acer | | Other | |
|---|---|---|---|---|---|---|---|---|
| | Online | Offline | Online | Offline | Online | Offline | Online | 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 | | Samsung | | Nokia | | Other | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Online | Offline | Online | Offline | Online | Offline | 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 6: Long-term price differences
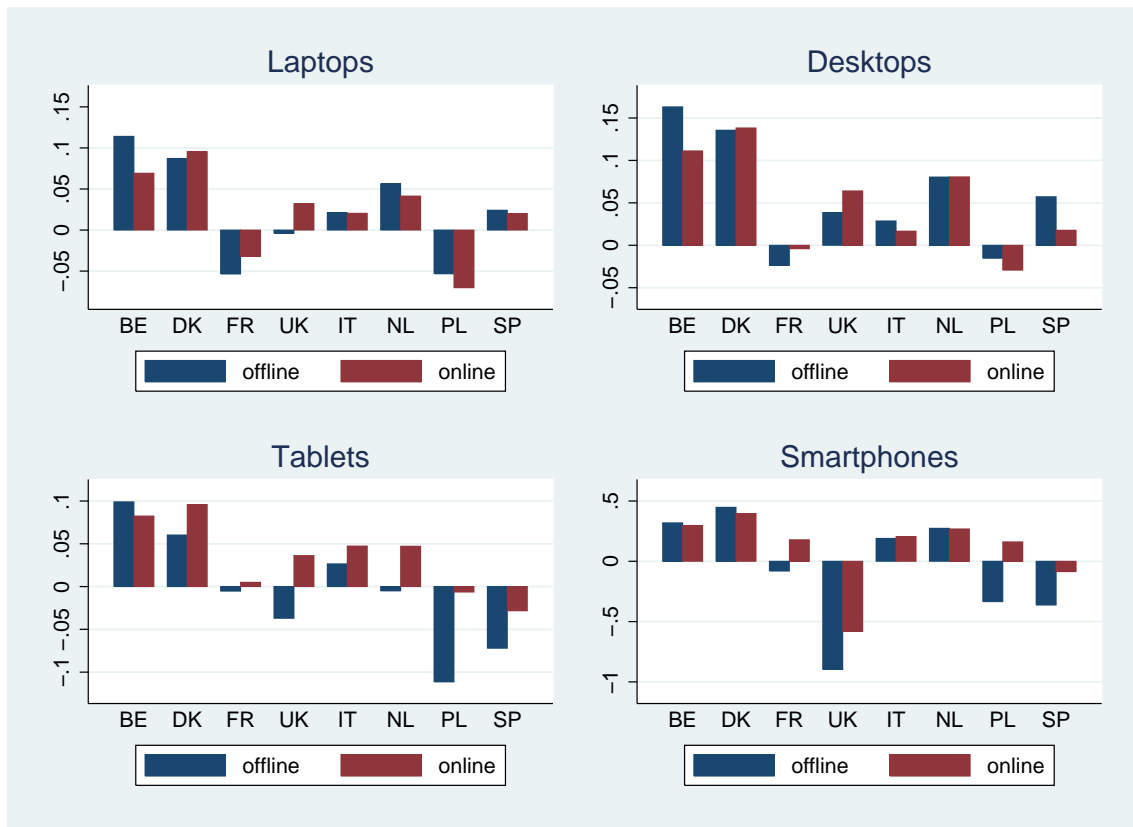
Notes: Long-term prie differences computed from $\alpha_c^k/(-\beta^k)$, based on the parameter estimates of convergence regression (1) including a set of product fixed effects shown in Table B.1.

# 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

| VARIABLES | Small | | | | Large | | | |
|---|---|---|---|---|---|---|---|---|
| | 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

| VARIABLES | Low-priced products | | | | High-priced products | | | |
|---|---|---|---|---|---|---|---|---|
| | 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.